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Abbring, J.H.; van den Berg, G.; van Ours, J.C.

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Jaap H. Abbring*
Gerard J. van den Berg†
Jan C. van Ours‡

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Abstract

In this paper, we study U.S. unemployment dynamics using grouped unemployment data from the Current Population Survey over the period 1968–1992. We estimate a model that traces variation in these unemployment data, both over time and between demographic groups, back to the underlying variation in the inflow and the outflow. In turn, we model the outflow as a transition process in which we allow the exit probabilities to depend on calendar time, duration, and demographic group. We particularly focus on the measurement and economic interpretation of the interaction of duration dependence of exit probabilities and the business cycle.

*Department of Economics, Vrije Universiteit (Free University), De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands. Phone: +31.20-444.6047. Fax: +31.20-444.6005. Email: jabbring@econ.vu.nl. Http://mail.tinbinst.nl/~abbring.

†Department of Economics, Free University Amsterdam, Tinbergen Institute, and CEPR.

‡Department of Economics, Tilburg University, CentER for Economic Research, and CEPR.

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1 Introduction

Over the last decades, macroeconomists have increasingly recognized the relevance of gross worker and job flows to the understanding of aggregate fluctuations in labor markets.[1] Large gross flows between labor market states coexist at each point in time, and dwarf the net changes in the stocks of workers and jobs in each state.[2] In particular, this is true for unemployment, which suggests that unemployment dynamics play a central role in the reallocation of labor, and therefore in macroeconomic dynamics.

In this paper, we study U.S. unemployment dynamics by analyzing the variation in the flows into unemployment and the aggregate unemployment duration distribution over time and between groups of workers. We apply a novel methodology to analyze grouped unemployment data from the Current Population Survey (CPS) over the period 1968–1992. These data provide discrete-time time-series on aggregate numbers of individuals in different unemployment duration classes and a limited number of demographic groups. This allows us to calculate, for each demographic group, the aggregate inflow into unemployment, and the aggregate outflow from different duration classes at each calendar time point. Thus, we can estimate models for the inflow, or incidence, and outflow. In particular, we explicitly model the outflow as a transition, or duration, process in which we allow the exit probabilities to depend on calendar time, duration, and demographic group in a very flexible way. Furthermore, in an extension we also investigate the role of (unobserved) cohort effects. The results allow for a complete decomposition of U.S. unemployment dynamics in a variety of incidence and duration components.

Our analysis addresses various issues from the ongoing empirical and economic-theoretical debate on unemployment dynamics. The first issue, cyclical variation of the incidence and the duration of unemployment, is hardly controversial. Unemployment incidence and duration are generally found to be countercyclical, leading to countercyclical unemployment. This is confirmed by our analysis.[3] Also, like the existing literature, we find upward trends in both incidence and duration.

The relative contribution of incidence and duration to the countercyclical variation in the unemployment rate leaves slightly more questions. The early literature finds that incidence fluctuations are particularly important in the 60s and the 70s, but the more recent papers attribute a dominant role to duration in the 70s and the 80s. It has both been argued that this difference is due to invalidity of the steady state assumptions used in the early literature, and that it reflects actual differences between the time periods considered. Our results are mildly in support of the more recent papers.

Another issue that raises controversy is the source of cyclical fluctuations in aggregate duration. Darby, Haltiwanger and Plant (1985) argue that durations are relatively stable

[1] See, for instance, Blanchard and Diamond (1992).

[2] See Blanchard and Diamond (1990) and Davis, Haltiwanger and Schuh (1996).

[3] See Section 2 for a more detailed review of the empirical literature.

at the disaggregate level, and that fluctuations are caused by fluctuations in the shares in the inflow of groups with different exit probabilities.[4] Baker (1992a) has dubbed this the "heterogeneity hypothesis". Darby *et al.* find some evidence for their hypothesis, but the few other papers that have pursued this issue reject it. We find that variation in the shares of the few demographic groups that we distinguish hardly generates any cyclicality of the aggregate exit probabilities. Conditional on demographic group, we do however find some evidence for cyclical cohort effects, *i.e.* cyclical variation with the moment of inflow. Such cohort effects can represent either (unobserved) compositional variation or variation of individual exit probabilities with the moment of inflow.

We also find significant cohort-specific and contemporaneous seasonal fluctuations in the exit probabilities, and considerable seasonality of the incidence. These results are novel, as the existing literature hardly discusses seasonal effects in the various components of unemployment.

The final and most debatable issue is the interpretation of the negative duration dependence that is observed in aggregate exit probabilities. Aggregate exit probabilities may exhibit duration dependence for a variety of reasons. If the exit probabilities of the members of a demographic group are duration dependent, duration dependence of the aggregate exit probabilities of the group results. Such duration dependence at the *individual* level can, for instance, be generated by limited benefit entitlement, loss of skills or stigma effects. However, even if individual exit probabilities do not vary with duration, *aggregation* over all members of a group will lead to duration dependence of the resulting aggregate exit probabilities if individuals within the group are heterogeneous with respect to their exit probabilities. This is due to the dynamic sorting of unemployed with low exit probabilities into long term unemployment.

In general, we should not expect the resulting duration dependence pattern to be invariant over calendar time, *i.e.* we should expect interactions between the duration dependence of exit probabilities and the business cycle. For instance, the sorting effects of aggregation are more severe, *i.e.* duration dependence is more negative, if exit probabilities are high. Also, duration dependence at the individual level will often interact with the business cycle. For instance, if, for any reason, a stigma is attached to long term unemployment, employers may rank applicants with respect to their unemployment durations, and hire those with the shortest durations. Such ranking is an example of interaction of agents in the labor market that generates negative duration dependence at the individual level. If relatively many jobs are available, the effects of such ranking may be less strong, and duration dependence less steep, because less applicants compete

[4]In particular, Darby *et al.* argue that two groups of individuals can be distinguished, one group with high transition rates into and out of unemployment, and one with a high degree of specific human capital and with long-duration jobs. In a recession, firms in declining industries find it optimal to accelerate labor force reductions, and the inflow into unemployment will consist to a relatively large extent of individuals in the second group.

for each job (Blanchard and Diamond, 1994, and Blanchard, 1991). This example suggests that the interaction effects are informative on the source of duration dependence. This is important, as different types of duration dependence have different allocative and macroeconomic implications.[5]

The evidence on interaction effects in the literature is very mixed. Apart from differences in data sets used, this could well be due to the restrictive specification of the interaction effects in this literature. One of the main distinguishing features of our analysis is that we allow for general interactions between calendar time and duration in our exit probability, or duration, model. In other words, we allow the entire duration distribution of unemployment, and not just some scale parameter, to vary over time in a general way. Alternatively, we could say that we allow for different business cycles at different durations. The interaction effects are flexible enough to capture processes like ranking and sorting, and more general asymmetries over the business cycle and durations. We find that the cyclical sensitivity of group-specific exit probabilities falls between the first and second months of unemployment, and rises thereafter. In the second and third month of unemployment exit probabilities are less responsive to the business cycle than in the first month; in later months exit probabilities are more responsive. We show that this is inconsistent with either pure ranking or pure sorting, and provide a simple model that combines ranking and sorting that generates this type of interaction pattern. It should be noted that we condition on a few demographic characteristics, thus explicitly modeling some sorting, and that the interaction effects are thought to capture any *additional* sorting because of unobserved heterogeneity. We do not seek to further quantitatively disentangle the various processes that drive aggregate duration dependence of the exit probabilities.

The CPS data used in this paper are fairly aggregated. The main advantage of such data is that they cover a much longer time span than is usual in micro data. Clearly, for reliable estimation of business cycle effects, it is necessary to have data that include at least a complete cycle. Another major advantage of aggregate data is that usually they do not suffer from attrition. In the analysis of labor market transitions, attrition is a particularly serious problem, since it is likely that the occurrence of a transition induces attrition (see Van den Berg, Lindeboom and Ridder, 1994). Finally, truly aggregate data in principle cover the whole population, which makes such data better suited for the analysis of the overall impact of aggregate events like business cycles.

Two closely related studies by Sider (1985) and Baker (1992a) use similar data from the CPS to study the effect of business cycles on the incidence and duration of unemployment. Sider (1985) focuses on the basic decomposition of secular and business cycle variation in unemployment in fluctuations in the incidence and duration, over the period 1968–1982. He does not consider any demographic variation, and uses a strongly param-

[5]See Blanchard (1991), Blanchard and Diamond (1994), and Section 6 of this paper.

eterized duration model, allowing only for interaction effects of limited flexibility. Baker (1992a) extends Sider (1985)'s analysis by performing similar analyses for a large variety of demographic groups, and adds an analysis of the shares of the demographic groups in the incidence. This allows him to directly address the heterogeneity hypothesis put forward by Darby, Haltiwanger and Plant (1985). Baker only analyzes expected durations constructed from the CPS data, and does not model the full duration distribution, *i.e.* the full set of exit probabilities. As a consequence, his analysis does not address the duration dependence and interaction issues. Neither author reports results on seasonal effects.

A related study by Imbens and Lynch (1992) uses micro data, taken from the National Longitudinal Survey of Youth (NLSY), on a sufficiently long time period, 1978–1989, to discuss business cycle variation of unemployment durations. The main advantage of their analysis over earlier studies, and our study, is that their data allow for a more detailed study of the heterogeneity hypothesis. However, the NLSY data only contain information on a specific group of young school leavers, and a much shorter time period than our more aggregate data. Also, Imbens and Lynch (1992) do not study the incidence, only provide very raw information on seasonal effects, and strongly parameterize the interaction effect. Thus, we view our results as complementary to the studies by Baker (1992a) and Imbens and Lynch (1992), which provide more direct information on the role of heterogeneity.

The plan of this paper is as follows. In Section 2 we provide a survey of the relevant empirical literature. Section 3 introduces the model. Section 4 discusses the data. In Section 5, we present the empirical results and provide a decomposition of U.S. unemployment dynamics. Section 6 provides an economic interpretation of the estimated duration dependence and interaction effects. Section 7 concludes.

2 A review of the empirical evidence

In this section we briefly review the numerous empirical studies examining the variation in unemployment incidence and duration.

The countercyclical nature of the unemployment rate can be traced back to variation in unemployment incidence and duration, both of which are generally found to be countercyclical.[6] Layard, Nickell and Jackman (1990) find that incidence and duration

[6] Darby, Haltiwanger and Plant (1985), Sider (1985), Blanchard and Diamond (1990), and Davis, Haltiwanger and Schuh (1996), Chapter 6, find that the incidence is countercyclical. Sider (1985), Darby Haltiwanger and Plant (1985), Butler and McDonald (1986), Dynarski and Sheffrin (1990), Blanchard and Diamond (1990), Imbens and Lynch (1992), Baker (1992a), and Davis, Haltiwanger and Schuh (1996), Chapter 6, provide evidence for the countercyclical nature of unemployment durations, or, stated differently, the procyclical nature of exit probabilities from unemployment. This line of research is rooted in research that focuses on the turnover in U.S. unemployment, *i.e.* on the average incidence and duration, and that is usually based on the CPS. For examples, see Kaitz (1970), Clark and Summers (1979), Akerlof and Main (1980, 1981), and Carlson and Horrigan (1983). Since the end of the 1970s, duration studies based on micro (panel and cross-section) data dominate in quantity over studies based on CPS data. The

contribute equally to the cyclicality of the unemployment rate over the period 1962–1989. However, like many of the earlier studies, their analysis is based on a steady state assumption, which is likely to overstate the relevance of the incidence.[7] Indeed, using non-steady state techniques, Sider (1985) finds that variation in durations is the dominant force driving unemployment rate cyclicality in the period 1968–1982. This is confirmed by Baker (1992a) for the period 1979–1988.

As noted in the introduction, the cyclicality of aggregate exit probabilities can either work by way of an effect on the composition of the inflow or by way of a direct effect on the individual outflow probabilities. Darby, Haltiwanger and Plant (1985) find some circumstantial evidence for their heterogeneity hypothesis in highly aggregate data. However, Dynarski and Sheffrin (1990), Imbens and Lynch (1992) and Baker (1992a) reject the heterogeneity hypothesis, and conclude that cyclical variation of the aggregate exit probabilities corresponds to underlying variation of individual exit probabilities. The first two studies use micro data while the third uses aggregate data containing a large number of observed explanatory variables. In these cases, certain attributes of the inflow are directly observed, and the heterogeneity hypothesis can be tested more directly.

The upward trend in the unemployment rate has been attributed to upward trends in both the incidence rate and unemployment duration.[8] In particular, Sider (1985) finds that around two thirds of the trend in the unemployment rate can be explained by an upward trend in durations, over the 1967–1982 period. Seasonal patterns in incidence and duration have attracted much less attention than longer run variation. Imbens and Lynch (1992) provide some evidence that unemployment durations are relatively short in the summer and long in the winter, in a sample of school leavers from the National Longitudinal Survey of Youth (NLSY) for the period 1978–1989. This is confirmed by Davis, Haltiwanger and Schuh (1996) using CPS data for the period 1972–1988. They find that the size of the outflow from unemployment is largest (smallest) in the June–August (December-February) quarter, and to a lesser extent the March–May (September–November) quarter.[9] The inflow is particularly large in the June-August quarter, and

focus in these studies has been, among other things, on differences in exit behaviour between groups of unemployed. See Devine and Kiefer (1991) for an overview.

The countercyclical nature of unemployment durations is justified theoretically in Van den Berg (1994), who generalizes previous theoretical papers by showing that, in job search models and under almost every possible configuration of the model determinants, the job offer arrival rate has a positive effect on the exit rate out of unemployment.

[7]This is an argument put forward by Sider to explain the differences between his results and results found in earlier studies. Baker (1992a) argues that the differences could also due to actual differences between the time periods considered.

[8]Data on this can be found Darby, Haltiwanger and Plant (1985), Sider (1985), Butler and McDonald (1986), Blanchard and Diamond (1990), Imbens and Lynch (1992), and Davis, Haltiwanger and Schuh (1996).

[9]Note that this cannot be compared to fluctuations in the exit rates from unemployment directly, as unemployment fluctuates over seasons as well.

small in the March–May quarter.

It is generally found that aggregate exit probabilities decline with duration.[10] Butler and McDonald (1986) find that the aggregate hazard first increases over the first 6 weeks of unemployment, and decreases thereafter, using grouped duration data from the Bureau of Labor Statistics (BLS) over the period 1948–1980. However, this result depends on a steady state assumption and parametric functional form restrictions. Imbens and Lynch (1992) find a similar result, with the peak occurring after 2 weeks, but their result only applies to the specific group of young workers in their NLSY sample.

As argued in the introduction, the variation of the aggregate duration dependence pattern with the business cycle is informative on the underlying dynamic processes. The evidence is mixed. Using grouped duration data for the first 4 months of unemployment from the CPS for the period 1968–1991, Van den Berg and Van Ours (1996) find negative interaction of duration dependence of aggregate exit probabilities with the state of the business cycle. Here, with "negative interaction" we mean that duration dependence is more negative when exit probabilities are high and durations are low, *i.e.* in the top of a cycle. They view this as evidence for dynamic sorting, caused by (unobserved) heterogeneity.[11] Sider (1995) also finds negative interaction: the exit probabilities at durations under 6 months are more responsive to business cycle fluctuations than the exit probabilities at durations longer than 6 months. However, within either the first 6 months or the later months, exit probabilities seem to be equally responsive to cyclical fluctuations. The absence of negative interaction during the first months is in conflict with the results of Van den Berg and van Ours (1996).[12] Butler and McDonald (1986) find that the cyclical sensitivity of aggregate exit rates increases with duration, *i.e.* positive interaction, in the first 7 weeks of unemployment, and negative interaction thereafter.[13] However, their results depend on strong parametric and steady state assumptions. Correcting for observed heterogeneity, and thus removing a source of negative interaction, Dynarski and Sheffrin (1990) find positive interaction. Imbens and Lynch (1992) find negative interaction at the aggregate level, and show that this result is robust to the introduction of regressors. Both papers parameterize interaction in a single parameter. The latter study uses data

[10] For instance, see Layard, Jackman and Nickell (1991) and Van den Berg and Van Ours (1996).

[11] Note that these results are derived separately for the same data on four demographic groups we use in this paper. Further aggregation over these groups can be expected to reinforce this result.

[12] It should be noted that the Van den Berg and Van Ours (1996) allow for fully non-parametric calendar time effects, whereas Sider (1985) uses single business cycle indicator without experimenting with lags or leads. On the other hand, Van den Berg and Van Ours (1996) estimate a model that, even though it is flexibly parameterized and allows for a wide range of interaction effects that are inconsistent with sorting, is in essence a dynamic sorting model.

[13] When controlling for proportional unobserved heterogeneity, and thus effectively taking away a source of negative interaction, they find increasing cyclical responsiveness of exit rates at all durations. Also, they summarize the overall interaction pattern in a single measure, the responsiveness of a measure of the concentration of the duration distribution to the business cycle, and conclude to positive interaction. However, the relation of this measure to the processes underlying interaction is not clear (see Section 6.

that cover a much longer time span than the former, but are also restricted to a specific group of individuals, young school leavers.

3 An empirical model of unemployment dynamics

3.1 Aggregate unemployment and exit probabilities

In this paper, we use aggregate time series of the number of unemployed by elapsed unemployment duration and a limited number of demographic types, or groups, from the CPS.[14] We will treat these data as being generated by a truly discrete time process. More formally, we take calendar time and duration to be discrete variables measured on scales that are the same, apart from a difference in origins. The duration of a spell of unemployment t for a given individual is measured from the moment the individual becomes unemployed. Calendar time τ has its origin somewhere in the past.

As an example, consider an individual who is unemployed for t periods at calendar time τ. If he fails to leave unemployment in period t, he will be unemployed for $t+1$ periods at calendar time $\tau+1$.

Thus, the CPS data are thought to provide estimates of the total numbers of individuals of type g in the labor market who are unemployed for t periods of time, $t = 0, 1, \ldots, K+1$, at calendar times $\tau_0, \tau_0+1, \ldots, \tau_0+N+1$. We denote these numbers by $U(t|\tau, g)$. From these numbers we can calculate the fraction $\theta(t|\tau, g)$ of the individuals of type g who are unemployed for t periods at calendar time τ who leave unemployment at τ:

$$\theta(t|\tau, g) = \frac{U(t|\tau, g) - U(t+1|\tau+1, g)}{U(t|\tau, g)}. \tag{1}$$

This fraction equals the aggregate exit probability out of unemployment in group g at calendar time τ and duration t, conditional on survival up to t.

3.2 The basic decomposition

Aggregate group g unemployment at time τ is given by $U(\tau, g) := \sum_{t=0}^{\infty} U(t|\tau, g)$, and aggregate unemployment by $U(\tau) := \sum_g U(\tau, g)$. Using (1), we can derive a decomposition of $U(\tau)$,

$$U(\tau) = U(0|\tau) + \sum_{t=1}^{\infty} U(0|\tau-t) \left[\sum_g \frac{U(0|\tau-t, g)}{U(0|\tau-t)} \prod_{i=0}^{t-1} (1 - \theta(i|\tau-t+i, g)) \right]. \tag{2}$$

[14]See Section 4 for details on the data set.

Consistently with the discrete time setup of our model, we take the number of unemployed in the first duration class $U(0|\tau,g)$ as our measure of the "incidence" of unemployment in group g. Then, $U(0|\tau) := \sum_g U(0|\tau,g)$ is the aggregate incidence at τ.[15] Thus, equation (2) provides a fully dynamic decomposition of unemployment in aggregate incidence and duration, or exit probability, components.

We illustrate this point with the steady state equivalent of this decomposition: if all variables are constant over calendar time τ, (2) reduces to

$$U(\tau) = U(0) \sum_g \frac{U(0|g)}{U(0)} \left[1 + \sum_{t=1}^{\infty} \prod_{i=0}^{t-1} (1 - \theta(i|g))\right], \tag{3}$$

where we have dropped the argument τ for obvious reasons. The factor between brackets is the expected unemployment duration of group g, which is aggregated over g into the aggregate expected unemployment duration. Thus, aggregate unemployment factorizes in an aggregate incidence and an aggregate duration component in steady state.[16] In turn, the duration component is one-to-one related to the exit probabilities from unemployment.

Our empirical approach consists of specifying and estimating models of the incidence and the exit probabilities that attribute fluctuations to various components related to duration, calendar time, and demographic group. Estimates of these models can then be used to assess the relevance of each component in explaining variation in unemployment duration and incidence, and in turn unemployment itself, using the dynamic decomposition of equation (2).

The fact that we model the duration probability distribution distinguishes our analysis from those in the closely related papers by Baker (1992), who uses the gross exit probabilities to compute expected aggregate durations, and subsequently only analyzes these durations.[17] Furthermore, we explicitly recognize measurement errors in the observed CPS unemployment statistics. In the next subsection we show that this results in a natural (non-linear) regression framework to estimate the different components in which we seek to decompose aggregate unemployment.

3.3 Measurement errors

In reality, we do not exactly observe the numbers $U(t|\tau,g)$. The CPS data we use are based on surveys of unemployed individuals. Therefore the data contain sampling errors.

[15]These variables are smaller than the continuous time inflow because it excludes the persons who enter and leave unemployment between two measurement points. In the literature both measurement methods have been used. For example, Sider (1985) tries to approximate the latter whereas Layard, Nickell and Jackman (1991) use the same method as we do.

[16]Note that unemployment also factorizes if we only impose steady state conditions on the aggregate incidence. We do however consider the full steady state for expositional reasons.

[17]Sider (1985) does analyze the exit probabilities, but imposes much more restrictions than we do.

Furthermore, respondents may have difficulties recalling their elapsed unemployment durations. In that case, they may be counted as being unemployed for t periods of time whereas in reality they are unemployed for $t-1$ or $t+1$ periods. Finally, respondents may tend to round off their duration to the nearest natural unit of time like an integer number of months (see also Section 4). Deviation of unemployment figures from their true values causes deviation of observed exit probabilities from their true values, and may even render these probabilities negative. Therefore, we will allow for measurement errors in the model. From now on we place a tilde on top of observed values, in contrast to true, or unobserved, values. We assume that

$$\widetilde{U}(t|\tau,g) = U(t|\tau,g)\,\varepsilon_{g,t,\tau} \tag{4}$$

with

$$\ln \varepsilon_{g,t,\tau} \sim N(0,\sigma_g^2) \tag{5}$$

and independence between the error terms. Note that we allow for heteroscedasticity between demographic groups.

From this specification, it follows that the observed $\ln\left(1-\widetilde{\theta}(t|\tau,g)\right)$ equals the sum of the true $\ln(1-\theta(t|\tau,g))$ and a disturbance term. In the sequel, we will provide a flexible model for $\theta(t|\tau,g)$. If we observe $\widetilde{U}(t|\tau,g)$ for $K+2$ duration classes $0,1,\ldots,K+1$, this generates $K+1$ different regression equations, for $\widetilde{\theta}(0|\tau,g)$ up to and including $\widetilde{\theta}(K|\tau,g)$. The loss of information when going from $K+2$ duration classes for U to $K+1$ equations for θ, which is a first difference of U, concerns the level of unemployment. This is accounted for by the equation for the log size of the total inflow into unemployment, *i.e.* $\ln \widetilde{U}(0|\tau,g) = \ln U(0|\tau,g) + \ln \varepsilon_{g,0,\tau}$.[18] In Section 5 we will specify a simple model for $U(0|\tau,g)$. Our primary focus in the remainder of this section will be on the less trivial task of specifying a duration model, *i.e.* a model for $\theta(t|\tau,g)$.

3.4 A model for aggregate unemployment durations

We assume that the true log exit probabilities are given by

$$\ln\theta(t|\tau,g) = \gamma(g) + \psi_1(t) + \psi_2(\tau) + \psi_3(\tau-t) + \xi_1(t)\xi_2(\tau), \tag{6}$$

where we require that $\xi_1(0)=0$ and $\xi_2(\bar{\tau})=0$, for some known $\tau_0 \le \bar{\tau} \le \tau_0+N$. Equation (6) specifies the aggregate exit probabilities of group g individuals as a very flexible function of the demographic group g, elapsed unemployment duration t, and calendar time τ. The model allows for both contemporaneous and cohort calendar time effects, and for general interactions between duration and calendar time dependence.

[18] Note that, even though the notation suggests otherwise, we will estimate the duration and incidence equations separately, without exploiting the relation between the error components.

We further structure the calendar time effects to reflect seasonal and longer run variation. Suppose that years are made up of $S \geq 2$ calendar time periods, so that any two calendar time periods τ and $\tau + S$ correspond to the same season in two consecutive years. The contemporaneous calendar time effect $\psi_2(\tau)$ is specified as the sum of a cycle and trend term $\psi_{2,c}(\tau)$ and a seasonal term $\omega_2(\tau)$:

$$\psi_2(\tau) = \psi_{2,c}(\tau) + \omega_2(\tau). \tag{7}$$

We restrict ω_2 to be periodical: $\omega_2(\tau) = \omega_2(\tau + S)$ for any τ. The longer run factor $\psi_{2,c}$ then reflects any variation at yearly and lower frequencies. We make similar assumptions on the moment in inflow, or cohort, effect ψ_3, which is assumed to be separable in a term $\psi_{3,c}$ representing longer run variation and a seasonal term ω_3. Finally, we exclude seasonal variation from the calendar time part of the interaction effect, $\xi_2(\tau)$, allowing only for variation of the duration dependence pattern at yearly and lower frequencies.

We will experiment with various specifications of the lower frequency effects. Details can be found in Subsection 5.1. A common feature of all specifications is that they exclude variation at higher than yearly frequencies. This ensures that all seasonal variation in durations is periodical, and captured by ω_2 and ω_3.

We will shortly review the main features of the model. First note that observed demographic characteristics only affect the exit probability through the group-specific constant $\gamma(g)$: for any two groups g and g'

$$\ln\theta(t|\tau, g') - \ln\theta(t|\tau, g) = \gamma(g') - \gamma(g),$$

for all t and τ.

The specification of the duration and calendar time effects can most easily be clarified by first abstracting from cohort, or moment of inflow, effects. So, for now suppose that $\psi_3 \equiv 1$. Then, at any time τ, and for any group g, duration dependence between durations t and t', defined as the change of the log exit probability between durations t and t', is given by

$$\ln\theta(t'|\tau, g) - \ln\theta(t|\tau, g) = \psi_1(t') - \psi_1(t) + \xi_2(\tau)\left(\xi_1(t') - \xi_1(t)\right). \tag{8}$$

For $\tau = \bar{\tau}$ the r.h.s. of (8) reduces to $\psi_1(t') - \psi_1(t)$. So, ψ_1 in (6) can be seen as the "baseline" duration dependence experienced at calendar time $\bar{\tau}$. Similarly, we can highlight the calendar time dependence of the log exit probability at any duration t, and for any group g, by

$$\ln\theta(t|\tau', g) - \ln\theta(t|\tau, g) = \psi_2(\tau') - \psi_2(\tau) + \xi_1(t)\left(\xi_2(\tau') - \xi_2(\tau)\right), \tag{9}$$

for any two times τ and τ'. For $t = 0$, this reduces to $\psi_2(\tau) - \psi_2(\tau')$: ψ_2 is the "baseline" (contemporaneous) calendar time dependence at duration 0. If ξ_1 and ξ_2 are not identically equal to 0, (8) implies that the pattern of duration dependence varies over calendar time, *i.e.* that there is interaction. In this case, calendar time dependence varies between duration classes, which is merely an instance of the same interaction effect.

As argued in the introduction, we are particularly eager to learn how the duration dependence pattern changes over the business cycle. To facilitate the discussion of the interaction effect, it is useful to introduce a measure of interaction that reflects this idea. To this end, we define the interaction effect between durations t and t' and times τ and τ', say $h(t,t';\tau,\tau')$, as the change in duration dependence between t and t' per log duration unit and unit change in $\psi_{2,c}$ between τ and τ', or

$$h(t,t';\tau,\tau') := \frac{(\xi_2(\tau') - \xi_2(\tau))\,(\xi_1(t') - \xi_1(t))}{(\psi_{2,c}(\tau') - \psi_{2,c}(\tau))\,(\ln(t'+1) - \ln(t+1))}, \tag{10}$$

for any $\tau, \tau' : \psi_{2,c}(\tau') \neq \psi_{2,c}(\tau)$ and $t' \neq t$.[19] If $h > 0$, duration dependence between t and t' is procyclical, in the sense that it is positively related to $\psi_{2,c}$. We will sometimes call this "positive interaction" (of duration dependence between t and t' with the business cycle between times τ and τ'). Similarly, we will say that there is "negative interaction" if $h < 0$, and "no interaction" if $h = 0$.

An unrestricted ξ_1 allows for "asymmetries over duration". If ξ_1 is increasing between durations t and t' and decreasing between durations t'' and t''', then $h(t,t';\cdot)$ and $h(t'',t''';\cdot)$ have opposite signs, and duration dependence between t an t' and duration dependence between t'' and t''' are negatively related over time. Equation (8) also shows that the general specification allows for "asymmetries over calendar time". If ξ_2 moves procyclically in one period and countercyclically in another period, the interaction effect changes sign between the two periods. From the perspective of cyclical responsiveness of the exit probabilities, an asymmetry over duration is reflected by a nonmonotonous relation between cyclical responsiveness and duration. An asymmetry over calendar time implies that the ranking of duration classes in terms of cyclical responsiveness changes over time. In particular, our specification restricts calendar time asymmetries to inversion of this ranking over time. More detailed examples of these asymmetries are given in Section 5.

Finally, we allow for variation of the aggregate exit probabilities with the moment of inflow $\tau - t$, which enter the model as ψ_3. Note that ψ_3 adds an additional interaction between τ and t, but one which cannot be generated by the interaction term because of the requirement that $\xi_1(0) = 0$. ψ_3 can represent either (unobserved) compositional variation or variation of individual exit probabilities with the moment of inflow. The former arises if the composition of the cohorts of each group g, in terms of the average exit probability, varies over time. This is the interpretation used by Abbring, Van den Berg, and Van Ours (1999). The latter results if the composition of the inflow is constant

[19]Note that $h(t,t';\tau,\tau')$ is undefined if $\psi_{2,c}(\tau') = \psi_{2,c}(\tau)$. If this is the case, and the enumerator in (10) is nonzero, then duration dependence has changed between τ and τ', even though the state of the business cycle is the same.

over time, and the individual exit probabilities depend on the moment of inflow $\tau - t$. De Toldi, Gouriéroux and Monfort (1992) take this approach to model the effect of the season at the moment of inflow.

As explained in the introduction, duration dependence at the level of a group g and interaction of such duration dependence with calendar time effects can both be generated by aggregation over heterogeneous members of the group g, or by duration dependence at the level of the individual members of g. An example of the latter that also generates interaction effects is ranking. Ranking explains individual duration dependence as the result of competition at the group g or aggregate level for jobs that are offered by firms that prefer short term unemployed over long term unemployed. It should be stressed that we will not seek to quantitatively disentangle all possible processes underlying duration dependence at the group level. Instead, we have specified (6) to be sufficiently flexible to represent the generated duration dependence patterns, including interactions. As some of the processes generating duration dependence, such as ranking and sorting, predict different interaction effects, we will however be able to determine which type of process dominates. We will discuss the issues of ranking and sorting in more detail in Section 6.

3.5 Some remarks on identification

We end this section with some remarks on identification. As a first remark, note that we have to normalize 5 terms out of γ, ψ_1, $\psi_{2,c}$, ω_2, $\psi_{3,c}$ and ω_3, and leave one term unnormalized to capture the scale of the exit probability.

A more substantial identification problem arises because our duration model includes both cohort $(\tau - t)$, contemporaneous calendar time (τ) and duration (t) effects. We can add a trend $f \cdot t$ to $\psi_1(t)$, a trend $-f \cdot \tau$ to $\psi_2(\tau)$, and a trend $f \cdot (\tau - t)$ to $\psi_3(\tau - t)$ without changing the image of $\psi_1(t)+\psi_2(\tau)+\psi_3(\tau-t)$, for any constant f. Thus, without further restrictions on ψ_1, $\psi_{2,c}$ and $\psi_{3,c}$, a trend term can freely be reassigned between ψ_1 and ψ_2 on the hand, and ψ_3 on the other, without changing the corresponding exit probability. In our main empirical estimates, we impose $\psi_{3,c} \equiv 1$, *i.e.* we exclude low frequency variation between cohorts, and this identification problem is immaterial. When we subsequently include longer run cohort variation in a sensitivity analysis of our main results, we make sure to always restrict $\psi_{3,c}$ sufficiently to avoid the problem.

A formal proof of non-parametric identification, using separability of seasonal and low frequency effects, exclusion of a trend from $\psi_{3,c}$, and appropriate normalizations, can be derived in the fashion of Abbring, Van den Berg and Van Ours (1999). In that paper, we formally exclude a trend from $\psi_{3,c}$ by assuming that $\psi_{3,c}$ is orthogonal to a linear trend. Similar assumptions are used in the consumption literature to identify time, cohort and age effects (Deaton and Paxson, 1993 and 1994). For further details, the reader is referred to these papers.

4 Data

To estimate our model we use unpublished CPS data from the Bureau of Labor Statistics (BLS) of the U.S. Department of Labor, which give monthly information on unemployment by weekly duration classes. Similar data from the same source have been used by Sider (1985), Baker (1992a) and Van den Berg and Van Ours (1996). We use data for 4 groups of workers, white males (wm), white females (wf), nonwhite males (nm) and nonwhite females (nf), over the period January 1968–May 1992.[20] For each month and each demographic group, the data provide the number of unemployed by unemployment duration in the "reference week", which is the week including the 12th of the month. Since the unemployment figures become more unreliable at longer durations we only use information for the first 6 months of unemployment.

As, for example, Sider (1985) and Baker (1992a) point out, there are several problems connected to the use of these data. First, the way in which the data are collected implies that we cannot follow actual cohorts over time. However, we may consider the data as synthetic cohorts. Second, the empirical analysis is much more straightforward if the frequency at which the data are collected equals the size of the unemployment duration classes. We aggregate the weekly duration classes into monthly duration classes. Third, the data are affected by phenomena like digit preferences and the tendency of respondents to report "weeks of unemployment" as whole months (Baker, 1992b). Because of this we make the same corrections as Baker (1992a), who reallocates 30% of the respondents at 4, 8, 12, 16 and 26 weeks, 40% of those at 52 weeks, and 50% of those at 78 and 99 weeks, in each month of the sample to adjacent later weeks. Finally, the data do not enable us to distinguish employment and transition out of the labor force as alternative destinations. However, Abowd and Zellner (1985) show that, on average, the share of workers becoming employed in the outflow from unemployment is larger than the share of workers leaving the labor force.

Figures 1–4 summarize some of the main features of our data, and provide a first impression of the unemployment experience of the 4 demographic groups. First, we have constructed aggregate unemployment time series by demographic group by aggregating the original data over the duration classes.[21] Figure 1 plots 12-month moving geometric averages of the resulting unemployment levels by demographic group.[22] The vertical lines

[20]The distinction between white and nonwhite individuals follows the racial categorization used by the BLS upto August 1989. From August 1989 onwards, the BLS reports whether individuals are white or black, and includes information on Hispanic origin. For this period, we have constructed unemployment levels for nonwhite males and females as the difference between the aggregate levels for all males and females and the levels for white males and females. This corresponds to the category "blacks and others", and not just "blacks", currently reported by the BLS.

[21]We have compared the resulting series to aggregate (group-specific) CPS series from the BLS website (`http://stats.bls.gov`). The differences are small and can be attributed to rounding errors.

[22]In the sequel, it is silently understood that we use *geometric* averages whenever we are dealing with

correspond to the NBER business cycle peaks (solid lines) and troughs (dashed lines) in the data period.[23] Unemployment for all groups is countercyclical, and the turning points in the unemployment series are generally close to the business cycle turning points. If anything, business cycle troughs lead unemployment peaks, and unemployment troughs occur slightly before business cycle peaks. There are also clear upward trends in the period upto the November 1982 business cycle trough, where the male trends are slightly steeper than the female trends.

Figure 2 plots moving averages of the corresponding unemployment rates.[24] The most obvious result is that nonwhite unemployment rates are persistently twice the white unemployment rates. Also, the upward trend in male unemployment, relative to female unemployment, in the 1970s and early 1980s is not an artefact of changing participation rates, and is also clearly present in the unemployment rates.

We can also provide a first impression of the underlying flow dynamics. Figure 3 plots moving averages of the inflow into unemployment as a fraction of the relevant labor force, for each demographic group. The differential in white and nonwhite incidence rates can explain a fair share of the unemployment rate differential. There is also clear evidence of countercyclical incidence rates, and at least some of the upward trend in male unemployment can be traced back to an upward trend in male incidence.

Note that, consistently with the discrete time setup of our analysis, we use the number of unemployed in the first duration class, $U(0|\tau, g)$, as our measure of the inflow (see Subsection 3.2). The corresponding discrete time measure of the outflow from group g unemployment at time τ is given by $U(0|\tau+1, g) + U(\tau, g) - U(\tau+1, g)$. Figure 4 plots this outflow from unemployment as a percentage of the level of unemployment for each of the 4 groups. The white-nonwhite outflow rate differentials are small compared to the unemployment rate differentials, and male-female outflow patterns do not show clear divergence of trends. We do however find that outflow rates are downward trending upto 1982 and procyclical, thus adding to the unemployment fluctuations identified earlier.

A more detailed picture of the underlying unemployment duration dynamics cannot be given using the simple techniques in this section. Due to large measurement errors in the data, raw pictures of, for instance, exit probabilities by duration class appear to be quite erratic. So, for a closer view of unemployment dynamics we have to estimate the duration model developed in the last section, thus explicitly dealing with the errors.

We end this section by inspecting the nature of the business cycle indicator $c(\tau)$ that we will occasionally use in our analyses, a (normalized log) help wanted index.[25] Data

positive variables.

[23]Source: Bureau of Economic Analysis, U.S. Department of Commerce, *Survey of Current Business, October 1994*, Table C51.

[24]We combine our aggregated data with CPS series of original group-specific civilian labor force levels from the BLS website (`http://stats.bls.gov`) to compute these rates. The same 4 series of labor force levels are used in the sequel.

[25]We have updated the series from Blanchard and Diamond (1989) using data from Citibase.

on this indicator are plotted in Figure 5, again with NBER business cycle reference dates included. The index closely follows the NBER cycle, although the timing of the turning points seems more in line with the unemployment cycle discussed above.

5 Empirical results

5.1 Some preliminary issues

In the duration model, we do not parameterize the baseline duration dependence and provide unrestricted estimates of the values of ψ_1. For the sake of parsimony, the seasonal effects ω_2 and ω_3 are parameterized as quarterly effects that are constant within the January-March, April-June, July-September and October-December quarters, but that can take different values between these quarters.

Our primary estimates will assume that there is no lower frequency cohort dependence of the exit probabilities, so that $\psi_{3,c} \equiv 1$. Although not strictly necessary for identification purposes, we impose this restriction to focus on flexible contemporaneous calendar time effects and interaction effects. We feel that by also including flexible cohort effects the model would not impose sufficient structure on the data to get proper inference. However, we investigate the robustness of the results under various specifications of $\psi_{3,c}$ in Subsection 5.3.

The baseline trend and cycle $\psi_{2,c}(\tau)$ is specified as a flexible polynomial of prespecified degree n:

$$\psi_{2,c}(\tau) = \sum_{i=0}^{n} \alpha_i p_i(\tau), \tag{11}$$

where p_0, $p_1, \ldots, p_n$ are mutually orthogonal polynomials of indexed degree.[26] Equation (11) provides a smooth representation of the lower frequency calendar time effects.[27] By

[26]More precisely, suppose that we consider our model for calendar time periods $\tau_0, \tau_0+1, \ldots, \tau_0+N$, for some $N \geq 1$. Consider the following linear transformation $\hat{\tau}$ from the calendar time domain $[\tau_0, \tau_0+N]$ to the interval $[-1,1]$:

$$\hat{\tau}(\tau) = 2\frac{\tau-\tau_0}{N} - 1.$$

We specify $p_i(\tau) = \hat{p}_i(\hat{\tau}(\tau))$, where the functions $\hat{p}_i$ are Chebyshev polynomials of the first kind, which are orthogonal on the *continuous* interval $[-1,1]$ (see Abramowitz and Stegun, 1970, Table 22.3):

$$\hat{p}_0(\hat{\tau}) = 1, \text{ and}$$

$$\hat{p}_k(\hat{\tau}) = \frac{k}{2}\sum_{i=0}^{\left[\frac{k}{2}\right]} (-1)^i \frac{(k-i-1)!}{i!\,(k-2i)!} (2\hat{\tau})^{k-2i}, \text{ for } i = 1, 2, \ldots, n.$$

[27]The use of series of orthogonal polynomials as smoothers is well known from the literature on nonparametric estimation. See, for instance, Härdle (1990), Section 3.3.

using *orthogonal* polynomials, we avoid multicollinearity between the polynomial terms. We will also try an alternative specification of $\psi_{2,c}(\tau)$, in which we specify $\psi_{2,c}(\tau) = \alpha_0 + \alpha_1 p_1(\tau) + \beta_2 c(\tau)$, where $c(\tau)$ is the log help wanted index (see Section 4).

As explained in Subsection 3.4, the most general specification of the interaction effect in the duration model allows for fairly complex asymmetries over calendar time and duration. We will further restrict the functions ξ_1 and ξ_2 to facilitate the interpretation of the interaction effect.

The simplest specification of $\xi_1(t)$ we use is $\xi_1(t) = \ln(t+1)$. In this case, the interaction effect in (10) reduces to

$$h(t, t'; \tau, \tau') = \frac{\xi_2(\tau') - \xi_2(\tau)}{\psi_{2,c}(\tau') - \psi_{2,c}(\tau)}.$$

This specification excludes all asymmetries over duration: the interaction effect only depends on τ and τ'. If $\xi_2(\tau)$ is tracking the cycle in the outflow, duration dependence will be less negative at all durations in the top of a cycle. If $\xi_2(\tau)$ is flexibly specified, it could be procyclical in one and countercyclical in an other period. Then, the interaction effect switches sign over calendar time. This is what we have labeled "asymmetry over calendar time" earlier.

Alternatively, we could specify the duration part of the interaction effect as

$$\xi_1(t) = \xi_{1,1}^* t + \xi_{1,2}^* t^2, \tag{12}$$

for some fixed parameters $\xi_{1,1}^*$ and $\xi_{1,2}^*$. This quadratic specification is more flexible, as it allows the interaction effect to vary with duration, *i.e.* for asymmetries over duration. More specifically, note that $\xi_1(t+1) - \xi(t) = \xi_{1,0} + \xi_{1,1} t$, where $\xi_{1,0} = \xi_{1,1}^* + \xi_{1,2}^*$ and $\xi_{1,1} = 2\xi_{1,2}^*$. Thus, the interaction effect concerning consecutive duration classes, $h(t, t+1; \cdot)$, is a linear function of t. This implies that $h(t, t+1; \cdot)$ will switch sign once if $\xi_{1,0} \cdot \xi_{1,1} < 0$, and will be either always nonpositive or always nonnegative otherwise. Also, $\xi_1(t) - \xi_1(0)$, and therefore $h(0, t; \cdot)$, is quadratic in t, so that $h(0, t; \cdot)$ switches sign once at some $t > 0$ if and only if $\xi_{1,0} \cdot \xi_{1,1} < 0$. As we will see in Section 6, both the variation of $h(t, t+1; \cdot)$ and of $h(0, t; \cdot)$ with t provide valuable information on the underlying processes. Therefore we will report both the values of $\xi_1(t) = \xi_1(t) - \xi_1(0)$ and the corresponding $(\xi_{1,0}, \xi_{1,1})$.

The simplest specification of the calendar time part of the interaction effect is $\xi_2(\tau) = \psi_{2,c}(\tau)$, and yields

$$h(t, t'; \tau, \tau') = \frac{\xi_1(t') - \xi_1(t)}{\ln(t'+1) - \ln(t+1)}.$$

This specification prevents the interaction effect to change over calendar time. For $t' > t$, the sign of $\xi_1(t') - \xi_1(t)$ can now directly be read as the sign of the interaction effect.

We will investigate asymmetries over calendar time by specifying ξ_2 more flexibly as

$$\xi_2(\tau) = \exp\left\{\sum_{i=0}^{n} \delta_i p_i(\tau)\right\}. \tag{13}$$

We have to check the nature of $\xi_2(\tau)$ before we can judge the interaction effect implied by $\xi_1(t)$. Clearly, if $\xi_2(\tau)$ is procyclical, the interaction effect has the same sign as $\xi_1(t')-\xi_1(t)$. Otherwise, it has the opposite sign.

Both $\psi_{2,c}(\tau)$ and, if specified according to (13), $\xi_2(\tau)$ are specified with $n = 15$. Furthermore, we normalize the seasonal effects in the duration model in the January-March quarter to 0. Apart from that, we normalize $\psi_1(0) = 0$, $\alpha_0 = \sum_{i=1}^{[n/2]} (-1)^{i+1} \alpha_{2 \cdot i}$, and $\delta_0 = \sum_{i=1}^{[n/2]} (-1)^{i+1} \delta_{2 \cdot i}$. The last 2 normalizations ensure that $\psi_{2,c}(\tau)$ and $\xi_2(\tau)$ equal 1 in the sample mean calendar moment, $\tau_0 + N/2$. Similarly, we take the help wanted index in log deviations from its value in the mean calendar time moment.[28]

Finally, we specify a simple model for the incidence. Similar to the log exit probabilities, and for each group g separately, we specify $\ln(U(0|\tau, g))$ as the sum of a 15-th order polynomial and a seasonal term $\omega_{g,4}(\tau)$. $\omega_{g,4}$ is specified like the seasonal terms in the duration model, but we do not restrict $\omega_{g,4}$ to quarterly fluctuations, and allow for general monthly effects. Note that we specify different models for different demographic groups to allow for shifts in the shares of these groups in the inflow into unemployment. We normalize the January effect in the incidence model for each group g to 0.

5.2 Parameter estimates

We estimate both the incidence and the duration models by maximum likelihood. In case of the incidence, this is a fairly trivial exercise, and we only report the seasonal effects in Table 1. There is significant monthly variation in the incidence, which is somewhat different between the demographic groups. The general pattern that arises is that the aggregate incidence is, on average, small in the January–March and October–December quarters, and large in the April–June and July–September quarters.[29] We graph the estimated longer run incidence rate developments by demographic group in Figure 6, again with vertical lines representing NBER business cycle peaks and troughs. To turn the group-specific incidence series implied by the incidence polynomial estimates into incidence *rate* series, we divide by 12-month moving averages of the group-specific labor force levels discussed in Section 4. Comparing the incidence rate fluctuations with the NBER business cycle reference dates and with the help wanted index in Figure 5, we find that the incidence rate is countercyclical, with male incidence being slightly more sensitive to the cycle. In Figure 7, we have plotted the implied cyclical and trend patterns in the shares of the four demographic groups in the incidence. The female shares on the one

[28] Note that we have implicitly chosen $\bar{\tau} = \tau_0 + N/2$.

[29] This follows from aggregating the seasonal effects over the demographic groups. Recall that our discrete time inflow at time τ is the stock of unemployed in the first duration class at τ. Therefore, it actually corresponds to the continuous time inflow in the interval $(\tau - 1, \tau]$. In contrast, the exit probabilities at time τ relate to the continuous time outflow in the interval $(\tau, \tau + 1]$. The second and the third quarter are however still the quarters with the largest incidence if we relate these to the May–July and August–October data on the incidence.

hand and the white male share on the other move countercyclically. The share of nonwhite males is hardly cyclical. There is a tendency towards a higher proportion of nonwhites in the inflow into unemployment. Furthermore, there is a mild upward trend in the share of white males relative to white females, but most of the convergence of male and female incidence rates can be traced back to an upward trend in the share of females in the labor force.

Table 2 contains estimates of four different specifications of the duration model. The first column contains estimates of the most flexible model, where $\xi_1(t)$ is assumed to have a quadratic specification. The second and third column show estimates of models in which we restricted $\xi_1(t) = \ln(t+1)$ and $\xi_2(\tau) = \psi_{2,c}(\tau)$, respectively. In the last column, the flexible specification of $\psi_{2,c}(\tau)$ as a polynomial is abandoned, and replaced by a more restrictive, but also more comprehensible combination of a linear trend and the business cycle indicator, the help wanted index.

A comparison of Columns 2–4 and Column 1 shows that most parameter estimates are hardly affected by the restrictions imposed. However, the restrictions are rejected by likelihood ratio tests at conventional levels of significance. In particular, the pseudo-R^2 statistics at the bottom of the table show that the fit of the last equation is negatively affected by the restrictions in Columns 2 and 3, and that the fit of all equations deteriorates if we use the most restrictive specification of Column 4. Therefore, we mainly restrict the discussion of the estimation results to the estimates presented in Column 1 of Table 2.

The differences between the four α_0-coefficients reflect the differences in exit probabilities between the demographic groups. Conditional on the state of the business cycle, the season and the duration of unemployment white female unemployed have the highest exit probability out of unemployment while nonwhite male unemployed have the lowest exit probability. There is a more pronounced difference between males and females than between nonwhite and white unemployed.

The estimates of $\psi_1(t)$ imply significantly negative duration dependence at all duration classes. The estimates of the α_2-coefficients indicate that there is calendar time fluctuation in the individual exit probability out of unemployment. As the parameter values of the polynomial are not very informative on the shape of $\psi_{2,c}(\tau)$, we have plotted this function in Figure 8. As explained earlier, $\psi_{2,c}(\tau)$ is the baseline cycle in the log exit probabilities from the first duration class (*i.e.*, at $t = 0$). At the baseline, the exit probabilities are clearly procyclical, which is confirmed by the significantly positive parameter on the help wanted index in Column 4.

The ω_2-coefficients reflect contemporaneous seasonal fluctuations in the exit probabilities. Labor market conditions seem to be most favorable in the Summer months: the exit probabilities are highest in the July-September quarter and lowest in the January-March quarter. The estimates of the ω_3-coefficients indicate that there is also seasonal cohort variation in the exit probability, which may be due to seasonal variation in the quality of the inflow conditional on the other determinants of the unemployment exit probability.

Unemployed that enter in the July-September quarter have the lowest exit probabilities while those entering in the January-March quarter face the highest exit probabilities. The reason for this may be increased competition with other newly unemployed in these quarters: recall that the incidence is large in the Summer quarters and small in the Winter quarters.

Interaction effects are generally significant. As ξ_2 and $\psi_{2,c}$ are positively related (see below), interaction is significantly negative in the first month, and significantly positive in later months (*i.e.*, $h(0,1;\cdot) < 0$, and $h(t,t+1;\cdot) > 0$ for $t \geq 1$). Figure 9 plots cycles and duration dependence $(\psi_1(t) + \psi_{2,c}(\tau) + \xi_1(t)\xi_2(\tau))$ in the log exit probabilities by duration class. Cyclical sensitivity falls between duration classes 0 and 1, but rises from $t = 1$ onwards. In duration classes 3 and 4, cyclical sensitivity is higher than in duration class 0 (*i.e*, $h(0,2;\cdot) < 0$, and $h(0,3;\cdot), h(0,4;\cdot) > 0$). Figure 10 offers a different angle by plotting duration dependence in log exit probabilities at $\xi_2(\tau) = 0.20$ and $\xi_2(\tau) = -0.20$, which roughly correspond to a boom and a recession period. In a boom, duration dependence is relatively high in the first month, but relatively low in the later months. We discuss a model based on sorting and ranking that generates such interaction patterns in Section 6.

The baseline calendar time cycle ($\psi_{2,c}$) and the cycle in the interaction effect (ξ_2) are in phase in the entire data period. Thus, we find no evidence of asymmetries of the interaction effect of the business cycle. However, as is shown by Figure 8, both cycles closely track each other in the first half of the data period, whereas the interaction cycle is substantially lower in the 1980s. This remarkable downward shift generates a tendency towards less duration dependence at low durations and more duration dependence at higher durations in the early 1980s.

5.3 Intermezzo: cyclical cohort effects in the duration model

So far, we have not allowed for cyclical cohort effects other than shifts in the shares of the observed demographic groups. Such cohort effects may be caused by unobserved changes in the composition of the inflow into unemployment over the business cycle, or by proper cohort effects on individual exit probabilities. As argued before, interaction between duration and cycle can be due to such cyclical cohort effects ($\psi_{3,c}$), and omitting $\psi_{3,c}$ may bias the other estimates. Therefore, as a robustness test of our results in Table 2, we have re-estimated both the preferred flexible model of Column 1 and the model with $\psi_{2,c}(\tau)$ depending on the help wanted index of Column 4, allowing for variation of $\psi_{3,c}(\tau - t)$ over the business cycle. We specify $\psi_{3,c}(\tau - t) = \beta_3 c(\tau - t)$, where $c(\tau - t)$ is again the log help wanted index. Because of the non-identification of an exponential trend in $\psi_{3,c}(\tau - t)$, we do not add a linear trend term, nor do we specify $\psi_{3,c}(\tau - t)$ as a polynomial series in $\tau - t$.[30]

Table 3 shows the estimation results. Both specifications produce strong procyclical effects of changes in the composition of the inflow on the exit probability from unemployment. We could interpret this as saying that the average unobserved quality of the inflow in booms is higher than the average quality of the inflow in slumps. Alternatively, there could be procyclical cohort effects at the individual level, *i.e.* for given individual charactistics.

Most other parameter estimates are not affected strongly by the introduction of cyclical cohort variation. The dummies for the demographic groups, the duration dependence estimates, the seasonal effects in the outflow and the seasonal cohort effects are practically the same. The coefficients of the interaction effects are somewhat affected, but the conclusion that there is negative interaction for lower duration classes and positive interaction for higher duration classes is still valid. Only the coefficients of the calendar time effect in the outflow have changed considerably. The coefficient on the help wanted index is 36% larger in the second column of Table 2 than it is in the corresponding column of Table 3. We will not further pursue the distinction between contemporaneous calendar time effects and (unobserved) cohort effects, and restrict attention to Table 2 in the sequel.

5.4 A decomposition of the unemployment rate

We finish this section by using our incidence and duration estimates to decompose cycles and trends in the aggregate U.S. unemployment rate. A problem in applying our empirical results in such an exercise is that we have not modeled exit probabilities for high duration classes. Consequently, we can not compute all components of aggregate unemployment in equation (2). Instead, we will use a "truncated" measure of unemployment that can be computed from data on $U(0|\tau, g)$ and $\theta(t|\tau, g)$, for $t = 0, \dots, n-1$, alone, unemployment in the first $n+1$ duration classes $U_n(\tau) := \sum_{t=0}^{n} U(t|\tau)$. Truncating equation (2) at $n+1$ months, we find

$$U_n(\tau) = U(0|\tau) + \sum_{t=1}^{n} U(0|\tau - t) \left[\sum_g \frac{U(0|\tau - t, g)}{U(0|\tau - t)} \prod_{i=0}^{t-1} (1 - \theta(i|\tau - t + i, g)) \right], \tag{14}$$

which now includes truncated duration components. We are particularly interested in the corresponding (truncated) unemployment rates, $u_n(\tau) = U_n(\tau)/L(\tau)$, where L is the aggregate labor force level.[31] Our estimation results allow for a formal decomposition of unemployment in the first 6 months, or u_5 ($n = 5$).

[30] Note that we could in principle include all but the linear polynomial terms in $\psi_{3,c}$, but this would demand too much from the data. See Abbring, Van den Berg and Van Ours (1999) for an analysis along these lines.

[31] We have aggregated the original group-specific civilian labor force levels used earlier over groups. Whenever we do not allow for seasonal effects in unemployment, we use 12 months moving averages.

We first investigate how much of the variation in the full unemployment rate, $u := u_\infty$, is captured by variation in u_5 in the raw data. Figure 11 shows that the gap between 12 months moving averages of u and u_5 varies between nearly nothing and 2%-points in the data period. The variance of $\ln(u_5)$ is 0.66 and the variance of the residual, $\ln(u/u_5)$, 0.05 of the variance of $\ln(u)$.[32] Although this suggests that most of longer run variation in the full unemployment rate can be attributed to u_5, it is clear that we cannot completely neglect variation in u/u_5 if we are ultimately interested in u. Although we cannot make a formal decomposition of u/u_5 for the reasons discussed earlier, we will provide a discussion of the decomposition of u, based on the the formal decomposition of u_5 and the raw data on u/u_5, at the end of this subsection. In particular, we will argue that most of the variation in u/u_5 should be attributed to the duration component of u, along with the duration component of u_5. We will now first discuss the formal decomposition of u_5, to which we will sometimes simply refer as "the unemployment rate".

We use the estimation results from Table 2, Column 1, and the estimation results for the incidence equations. These estimates can be substituted into equation (14) to compute various "counterfactual" aggregate unemployment series, *i.e.* unemployment series that would have occurred if some of the components of unemployment would have been eliminated, without changing the other components. We can for instance focus on the cycles and trends in the unemployment rate by fixing all seasonal terms at their geometric means.[33] Figure 12 plots unemployment rate (u_5) data, the unemployment rate predicted by the full model (including seasonal effects), and the unemployment rate predicted by the model from which all seasonal effects are eliminated. The latter is the unemployment rate series we seek to decompose, and will generally be referred to as the "full cycle". The fit of the predicted unemployment rates to the data is good. The variance of the full log model series is 0.95 of the variance of the log data, and the variance of the residual between the log data and the full log model is only 0.10 of the log data variance (note that this leaves a small covariance term of -0.05). In terms of their variance, the seasonal effects are relatively unimportant. The variance of the log full cycle is 0.89 (0.94) and the residual seasonal variance is only 0.18 (0.06) of the log data (full model) variance, leaving a small relative covariance term of -0.07 (0.00).

In the sequel, we focus on the decomposition of the full unemployment rate cycle. It should be clear from equation (2) that this dynamic decomposition is not (log)linear in the components, so that we cannot provide a simple variance decomposition. Instead, we decompose the full cycle by eliminating one-by-one the various components of unemployment and computing "remaining unemployment cycles" corresponding to cyclical

[32]The remaining 0.29 corresponds to the covariance term. Note that we again use moving averages to focus on longer run variation.

[33]More in general, we aim to preserve the geometric means of the exit probabilities in each duration class and the aggregate incidence whenever fixing a component of the model, except when fixing duration dependence (see below).

variation in the remaining components from equation (14). These remaining cycles can then be graphed with the full cycle to allow for an eyeball assessment of the (partial) contribution of the eliminated component to the full cycle. Also, we will provide with each such exercise a more formal decomposition of the variance of the log full cycle in the variance of the log remaining cycle, the variance of the residual (which can be contributed to the eliminated component), and a covariance term. Table 4 provides the various variance decompositions. In parentheses, we have added variance decompositions using the linearly detrended log full and remaining cycles. These decompositions address the proper cyclical variation of the unemployment rate, in isolation from any trends. Differences with the original decompositions are negligible, except for the duration dependence and interaction decompositions (see below). We will now discuss the decomposition exercises one at a time.

The primary decomposition of the unemployment cycle is in an aggregate incidence cycle on the one hand and all cyclical components of aggregate duration on the other. As is clear from equation (14), the latter are the cycles in the shares of the demographic groups in the incidence and the contemporaneous cycle, including interaction effects, in the exit probabilities. Figure 13 shows the effect of eliminating the aggregate incidence rate cycle.[34] Figure 14 graphs the result from the complementary experiment of eliminating all cyclicality from the exit probabilities. Note that the two experiments do not overlap, and together cover all cyclicality in unemployment. The graphs confirm that both procyclical outflow and countercyclical incidence drive the countercyclical variation in unemployment. The first two rows of Table 4 suggest that 35% of the cyclical variance of the unemployment rate can be attributed to the incidence cycle, and 20% to the outflow cycles. The remaining 45% is due to the reinforcing effect of the interaction of the incidence and outflow cycles.

Although the rounded figures in Table 4 suggest otherwise, the two variance decompositions are not the exact mirror images that one would expect in a (log)linear variance decomposition. There are some differences in the higher digits, which should be expected because of the non-linear nature of the dynamic decomposition. However, the fact that these differences are extremely small suggests that dynamic interactions between aggregate incidence and aggregate duration cycles are not very important. To provide some intuition for this result, recall from Subsection 3.2 that unemployment factorizes in an incidence and a duration component if the aggregate incidence is in steady state. As we focus on longer run fluctuations, cycles are roughly constant within a few months, and we are only considering the first 6 months of unemployment in our decomposition, dynamic interactions between incidence and duration cycles in equation (14) are necessarily small. Thus, a standard loglinear variance decomposition is a good approximation.

We can further decompose the longer term variation in aggregate durations in contemporaneous and compositional effects. As the dynamic interaction of aggregate duration

[34] Whenever we eliminate the aggregate incidence cycle, we also fix the labor force at a constant level. Note that the labor force series is hardly cyclical.

cycles and the incidence is numerically unimportant, we restrict attention to a decomposition of the variance of the "full outflow cycle" in the unemployment rate, *i.e.* the unemployment rate that results from eliminating the aggregate incidence cycle. The second panel of Table 4 shows the results from either fixing the contemporaneous cycle in the outflow, including the interaction effects, or the demographic shares in the incidence at constant levels. Note that, again, both experiments do not overlap and together cover the full outflow cycle in the unemployment rate. We find that nearly all effects of the outflow cycles on the unemployment rate are due to the contemporaneous outflow cycle. This should come as no surprise, as compositional effects on aggregate exit probabilities are only second order, stemming from the interaction of incidence share variation and heterogeneity in the exit probability between groups.

A final issue, the role of the interaction effects and duration dependence, is explored in the next two panels of Table 4. We depart from the unemployment rate cycle corresponding to contemporaneous exit probability fluctuations only, and first eliminate the interaction effects, and then also the (average) duration dependence.[35] Figure 15 graphs the resulting unemployment rate series. The unemployment rate variance increases after eliminating interaction effects and duration dependence. This is reflected in variances of the remaining cycles that are larger than the variance of the original series, and negative covariances. These results persist, although less pronounced, after we correct for linear trends. As can be seen in Figure 15, interaction effects and duration dependence dampen the upward trend in unemployment durations. The bottom panel shows that all these effects can be traced back to eliminating the interaction. Eliminating (average) duration dependence from a model with only a contemporaneous exit probability cycle without interaction effects hardly makes any difference. Again, this should come as no surprise, as in our computations the effects of (average) duration dependence on unemployment durations are only second order, resulting from the interaction of changes in the unemployment duration distribution and differences in exit probability levels between duration classes.

We finish by translating these results into results on the full unemployment rate u. First, note again that u simply decomposes loglinearly as $u_5 \cdot (u/u_5)$. We have already formally decomposed u_5 in incidence and duration components. In the dynamic setup of equation (14), u/u_5 also contains both types of components. However, we know that u and u_5 factorize in incidence (rate) and duration components if the aggregate incidence is constant for the relevant cohorts. Then, $U(0)$ cancels from u/u_5, and u/u_5 is a pure duration factor. Obviously, if survivors from very old cohorts matter numerically for current unemployment, we can only use this results if we are willing to assume that

[35] For each group g, we fix the geometric mean exit probability in each duration class at a level $\bar{\theta}(g)$ that corresponds to the same (truncated) expected duration as the geometric mean exit probabilities by duration class for that same group, say $\bar{\theta}(0|g), \bar{\theta}(1|g), \ldots, \bar{\theta}(4|g)$, in the full cycle model. Thus, for given $\bar{\theta}(0|g), \bar{\theta}(1|g), \ldots, \bar{\theta}(4|g)$, $\bar{\theta}(g)$ is implicitly given by $\sum_{t=1}^{5} \left(1 - \bar{\theta}\left(g\right)\right)^{t} = \sum_{t=1}^{5} \prod_{i=0}^{t-1} \left(1 - \bar{\theta}\left(i|g\right)\right)$.

incidence is nearly constant over long periods of time. However, using data on the first 6 quarters of unemployment (n=17), we find that u_{17} nearly exhausts all of u: the variance of $\ln(u_{17})$ is 0.94 of the variance of $\ln(u)$, and the variance of the residual is only 0.00 (leaving a covariance term of 0.06). Thus, u/u_5 is well approximated by u_{17}/u_5, which only covers 18 monthly cohorts of unemployed. As we are decomposing cycles that are supposed to capture fluctuations at yearly frequencies and lower, we can expect that interactions between incidence and duration in u/u_5 are small, so that most of the variation in u/u_5 can be attributed to duration.

We employ this idea in a formal decomposition of u. As u is loglinear in u/u_5 and u_5, we again find a nearly loglinear variance decomposition, which is shown in the last panel of Table 4. With both the u/u_5 moving average cycle and the outflow cycles in u_5 classified as duration components, duration accounts for 0.31 and incidence for only 0.23 of the $\ln(u)$ variance. Although this is an upper bound to the contribution of duration, it seems safe to say that at least half of the cyclical variation in the full unemployment rate can be attributed to duration. If we interpret u/u_5 as a pure duration factor, and distribute the covariance term proportionally, we attribute 57% of the log unemployment rate variance to duration, and 43% to the incidence rate.

We have seen that the mechanics of duration dependence and the composition of the inflow are of only second order importance to the dynamics of aggregate unemployment durations. It should however be noted that our decomposition exercise is by no means "structural", *i.e.* based on economic theory, and, in itself, does not address the *economic* relevance of issues like duration dependence. The fact that the economic relevance of duration dependence may go well beyond the mechanics of this section is explored in the next section.

6 An interpretation of the interaction effect: ranking versus sorting

We have established that exit probabilities aggregated at the level of demographic groups fall with elapsed unemployment duration. Furthermore, there is negative interaction of this duration dependence with the business cycle at low durations, and positive interaction at higher durations.[36] In this section, we discuss the two possible causes of aggregate duration dependence discussed in the introduction, ranking and sorting, and provide a model that combines both processes and that is consistent with the empirical results above.

Observed negative duration dependence could be driven by negative duration dependence at the micro level. In a world with asymmetric information, high unemployment

[36]Further aggregation over groups can be expected to generate more negative duration dependence, and, to some extent, more negative interaction. See below for details.

durations may signal low worker quality, and direct links between unemployment duration and worker productivity may exist if skills deteriorate when unemployed. In either case, employers prefer to hire short-term unemployed over hiring long-term unemployed. Then, in a nonsequential search environment, employers will rank applicants with respect to their unemployment durations, and hire those with the shortest durations. Such ranking is an example of interaction of agents in the labor market that generates negative duration dependence at the individual level.[37]

As argued in Section 1, sorting also causes negative duration dependence of observed exit probabilities. A crucial difference between ranking and sorting is that ranking is caused by variation in elapsed unemployment durations, whereas sorting is driven by variation in innate characteristics, like ability, and characteristics that can be considered given in the short run, like education. As a result, ranking and sorting have different dynamic implications. In a pure sorting model, unemployment exit rates of short-term unemployed are more sensitive to cyclical fluctuations than exit rates of long-term unemployed.[38] In a pure ranking model, exit rates of long-term unemployed are more sensitive to cyclical fluctuations than exit rates of short-term unemployed (Blanchard, 1991, and Blanchard and Diamond, 1994). By studying the interaction between cyclical fluctuations and exit rates at different unemployment durations we can distinguish between ranking and sorting.

This distinction is important as ranking and sorting have different allocative and macroeconomic implications. In case of pure sorting, long-term unemployment is concentrated in certain segments of the labor market. This may be undesirable and call for government intervention targeted at these specific segments. Pure ranking, on the other hand, is not necessarily discriminative between segments of the labor market. Instead, it is a future risk borne equally by all newly unemployed at each point in time. It could, however, be related to real economic costs of long-term unemployment. If ranking is driven by loss of skills during unemployment, prolonged spells of unemployment lead to excessive loss of human capital. Similarly, even if ranking is based on a mild loss of skills it could induce demotivation among long-term unemployed. In either case, the government

[37]See Blanchard and Diamond (1994) and Blanchard (1991). One may argue that, within markets, employers rank on both unemployment duration and skills. In that case, ranking is not rationalized by loss of skills, but by the fact that long-term unemployed are more likely to be screened and rejected by other employers in the same market. This idea has been formalized by Lockwood (1993), who develops a matching model with asymmetric information on worker productivity and imperfect screening. His results are not fully compatible with the results from the ranking model. It should be noted, however, that the mechanics of the models differ: in the ranking model employers search nonsequentially, whereas in Lockwood (1991) firms search sequentially. In this paper, we restrict attention to the ranking framework. Abbring and Van Ours (1994) provide empirical evidence that firms indeed search nonsequentially.

[38]See the Appendix. Van den Berg and Van Ours (1994, 1996 and 1997) and Abbring, Van den Berg and Van Ours (1997) analyze pure dynamic sorting models, and discuss the role of such interaction effects in identifying unobserved heterogeneity.

may want to direct policy to prevent the emergence of long-term unemployment.

The difference in macroeconomic implications of both models is related to the allocative differences. In case of ranking, newly unemployed face better employment prospects than the currently unemployed. Thus, in labor markets where the currently employed bargain over wages with employers, the presence of long-term unemployed has little effect on wages. Consequently, even if ranking is based on a mild loss of skills it may cause demotivation of long-term unemployed and thus considerable persistence in unemployment (Blanchard, 1991). In a sorting model, however, the presence of long-term unemployed can be expected to weaken the effect of the level of unemployment on wages, just like overall unemployment does (Blanchard and Diamond, 1994). As, in this case, prolonged unemployment does not necessarily weaken the effect of unemployment on wages, sorting is less likely to be associated with unemployment persistence.

To explain the relation with our empirical results, we develop a more formal model that incorporates both ranking and sorting. We do not claim that this model provides a perfect description of the labor market. Rather, it provides a consistent description of a labor market in which ranking and sorting can be distinguished.

Sorting occurs if there is variation across individuals in the level of the exit rate from unemployment. The main assumption of this subsection is that all of this variation can be traced back to labor market segmentation. We assume that the labor market is segmented in, possibly uncountably many, unrelated submarkets or segments and that each individual searches in only one segment. Exit rates from unemployment may vary between the submarkets, but within segments each individual with the same unemployment duration has the same exit rate to employment. Clearly, both from the perspective of supply and demand this assumption can be criticized. For example, it seems that, in practice, there is no supply segmentation of the labor market in submarkets for able and less able people, although ability may be related to the exit rate to employment. On the demand side, one could argue, workers from various segments may, for instance, be complements in the production process, which implies that hiring decisions in the various segments may be related. Our full segmentation assumption does not allow for such interaction between submarkets. On the other hand, it is not unreasonable to assume that segments exist for, for example, schooling, as, certainly in the short run, individuals cannot move from one schooling segment to the other. Furthermore, the segmentation assumption greatly facilitates the introduction of ranking into the model framework. Ranking occurs if, for whatever reason, firms prefer to hire short-term unemployed. Due to the full segmentation and homogeneity within segments, the Blanchard and Diamond (1994) model is directly applicable to each of the submarkets. Thus, we have ranking within segments, and sorting between segments.[39]

[39] Note that the previous empirical literature on unemployment dynamics does not make segmentation assumptions. This is because this literature is not concerned with ranking, which is based on employers' behaviour and therefore needs assumptions on market structure. Our empirical model does however

Unemployment duration t is again measured on a discrete time scale with origin 0. Suppose that segments can be characterized by a scalar $v \in (0, \infty)$. The probability of an individual leaving unemployment in segment v at unemployment duration t, conditional on survival up to duration t and state of the business cycle c, is given by

$$\vartheta\left(t|c, v\right) = \eta\left(c, t\right) v. \tag{15}$$

The individual exit probability is proportional in $\eta(t, c)$, which represents business cycle and duration dependence of individual exit probabilities, and a segment specific effect v. Note that $\eta(c, t)$ is common to all individuals within a segment v. The distribution of individuals over the segments v reflects all heterogeneity across unemployment durations, apart from random variation in these durations. We denote the distribution function of unemployed over the segments v by $G(v)$. As $\vartheta(t|c, v)$ is a probability, $G(v)$ is required to satisfy $\Pr[0 < \vartheta(t|c, v) < 1] = 1$. Suppose that $\eta(c, t)$ is differentiable with respect to c, where $\eta_c(c, t) > 0$: individual exit probabilities are higher at higher values of the business cycle indicator. If employers do not rank applicants according to t, but hire randomly, individual exit probabilities do not change with duration: $\eta(c, t + 1) = \eta(c, t)$ and $\partial \ln[\eta(c, t + 1)/\eta(c, t)]/\partial c = 0$. Ranking, however, implies that individual exit probabilities decrease during unemployment; $\eta(c, t + 1) < \eta(c, t)$. Moreover, within segments the labor market is homogeneous, so it follows from Blanchard (1991) and Blanchard and Diamond (1994) that in case of ranking:

$$\frac{\partial \ln\left[\eta(c, t + 1)/\eta(c, t)\right]}{\partial c} > 0, \quad \text{or} \quad h(t, t + 1; \cdot) > 0. \tag{16}$$

Thus, duration dependence caused by ranking is less steep in a boom, when c is relatively large. In other words, exit probabilities from unemployment are more sensitive to business cycle fluctuations at higher durations. These are the two faces of what we have labeled positive interaction before.

Now consider the effect of sorting. The aggregate exit probability in a cohort of workers that has become unemployed some time t ago, in a state of the business cycle c, equals[40]

$$\vartheta\left(t|c\right) = \eta\left(c, t\right) \nu\left(c, t\right), \tag{17}$$

where $\nu(c, t) := \mathbb{E}\left[v|c, T \geq t\right] = \mathbb{E}[v(1-\eta(c)v)^t]/\mathbb{E}[(1-\eta(c)v)^t]$. Note that $\nu(c, 0) = \mathbb{E}[v]$. If the distribution of v is degenerate, *i.e.* if all workers are concentrated in a single segment, $\nu(c, t) = \mathbb{E}[v]$, $\nu_c(c, t) = 0$ and $\nu(c, t+1) = \nu(c, t)$. In this case, there is no sorting, as workers are homogeneous. Now suppose that $\text{var}(v) > 0$. Then, workers are heterogeneous, and sorting will occur and cause negative duration dependence at the aggregate level: $\nu(c, t+1) < \nu(c, t)$. In the Appendix it is shown that sorting implies that duration

contain the models in this literature as special cases.

[40] We use uppercase fonts for random variables and lowercase fonts for their realizations, only if there is a risk of confusion. The Appendix provides details.

dependence between durations 0 and t is steeper in booms: $\partial \ln[\nu(c,t)/\nu(c,0)]/\partial c < 0$, or $h(0,t;\cdot) < 0$, for any $t > 0$. As, by implication of (16), in case of ranking

$$\frac{\partial}{\partial c} \ln \frac{\eta(c,t)}{\eta(c,0)} = \sum_{i=1}^{t} \frac{\partial}{\partial c} \ln \frac{\eta(c,i)}{\eta(c,i-1)} > 0, \quad \text{or} \quad h(0,t;\cdot) > 0, \tag{18}$$

a test can be based on $h(0,t;\cdot)$, the "cumulative" interaction effect. A measure of the overall cumulative interaction effect in our combined ranking-sorting labor market is found by taking the derivative with respect to c of the log exit probability at time t, relative to the exit probability at time 0, as in

$$\frac{\partial}{\partial c} \ln \frac{\vartheta(t|c)}{\vartheta(0|c)} = \frac{\partial}{\partial c} \ln \frac{\eta(c,t)}{\eta(c,0)} + \frac{\partial}{\partial c} \ln \frac{\nu(c,t)}{\nu(c,0)}. \tag{19}$$

The sign of the overall cumulative interaction effect is determined by the relative importance of ranking and sorting. So, a test on ranking versus sorting can be constructed from interaction data by evaluating (19) at various durations, testing for the sign of the interaction effect at each duration. Clearly, both sorting and ranking may occur simultaneously in the data. Then, the test merely gives the dominant process up to each unemployment duration.

Our result that $h(0,t;\cdot) < 0$ for low t is only consistent with sorting. As our interaction results are conditional on demographic group g, this should reflect additional heterogeneity on top of the differences between the four demographic groups we have considered. Sorting cannot explain that $h(0,t;\cdot)$ turns positive for higher t. However, dynamic sorting effects typically vanish at higher durations, as the sorted cohort becomes increasingly homogeneous. So, if there is ranking within segments, the corresponding positive interaction effects may well be dominated by negative sorting effects at low durations, but show up at higher durations. Thus, our simple model of sorting between segments and ranking within segments can generate the observed interaction pattern.

If we abandon our stylized model of ranking and sorting, theoretical results become less clear cut. Lockwood (1991) argues, using the matching model with sequential search to which we referred earlier, that the cut-off duration used by firms that discriminate against long-term unemployed varies over the cycle. This causes the same type of duration dependence and business cycle interaction as generated by the sorting model. As argued earlier, part of the differences with the ranking model can be traced back to differences in firm search behaviour. In any case, these results can only raise doubt about the interpretation of negative interaction, and ranking is still identified from the data. Lebon (1993) shows that, in a labor market with loss of skills during unemployment, firms are likely to rank in booms, but randomly hire in recessions. Blanchard (1996) focuses on the effect of wage differentials between short-term and long-term unemployed, and concludes the opposite. In our empirical model we have accounted for this by allowing for asymmetries in interaction effects over the business cycle. In Subsection 5.2, we have seen that there is no evidence of such asymmetries in the U.S. data.

7 Conclusions

We conclude with a summary of our main results. We have re-established that both aggregate unemployment incidence rates and durations are countercyclical and upward trending, thus contributing to similar fluctuations in the aggregate unemployment rate. Cyclical variation in unemployment durations accounts for at least half of the variance of cyclical variations in the log unemployment rate. This is roughly consistent with the results presented by Sider (1985) and Baker (1992a), but at odds with the earlier literature.

Our preferred estimation results attribute all cyclical variation in aggregate durations to contemporaneous variation of the aggregate exit probabilities. Cyclical variation of the shares of males and females and nonwhites and whites does not contribute at all. We find both significant exit probability differentials between these groups, in particular between males and females, and cyclical variation in the shares of these groups in the incidence. However, as the effects on the aggregate exit probabilities are only second order, they are negligibly small. From this we could conclude that the heterogeneity hypothesis by Darby, Haltiwanger and Plant (1985) is rejected, which would be in line with most of the literature. However, we have only controlled for a very limited number of individual characteristics in our decomposition analysis, and we cannot exclude significant compositional effects related to other individual characteristics. Indeed, a sensitivity analysis of our preferred results provides some evidence of unobserved cohort effects in the exit probabilities, and suggests that these explain at least some of the variation in aggregate unemployment durations. We can argue, though, that compositional effects are second order in any case, so that this would require large unobserved differentials between individual exit probabilities and large fluctuations in the shares of the different individuals in the incidence. Therefore, if large, such unobserved cohort effects are more likely to be due to proper cohort effects at the individual level.

There are also substantial seasonal fluctuations in U.S. unemployment. Exit probabilities are low in the first and high in the third quarter. Furthermore, unemployed entering in the first quarter have relatively short unemployment spells, whereas unemployed entering in the third quarter experience relatively long spells. As unemployment incidence is relatively small in the first and large in the third quarter, we conclude that this may be related to competition among unemployed. The seasonal effect estimates are consistent with the sparse evidence in the literature.

Finally, we find that the individual exit probabilities out of unemployment decline over the duration of the unemployment spell. This negative duration dependence is a quantitatively unimportant determinant of unemployment variation. We provide a detailed picture of the interaction of duration dependence in aggregate (group-specific) exit probabilities with the business cycle. In booms, duration dependence tends to become stronger (more negative) at low durations, and less strong (less negative) at higher durations. This is an asymmetry of interaction effects over duration. We do not find any asymmetries over calendar time, *i.e.* interaction effects changing signs in the course of time. This is in conflict with the predictions of some theories of unemployment dynamics (see Section 6). It should be noted that these results are derived conditional on observed demographic group. Aggregating would add more duration dependence and more negative interaction.

We discuss two economic processes that generate aggregate duration dependence and interaction effects, ranking and sorting. Neither process can, by itself, generate the empirical interaction patterns. However, we provide a model that combines sorting and ranking that can. Taking this model literally, we should conclude that there is considerable (unobserved) exit probability heterogeneity between individuals, and that dynamic sorting of heterogeneous individuals out of unemployment dominates at low durations. At higher durations, cohorts of unemployed are more or less sorted, consisting only of fairly homogeneous individuals with relatively low exit probabilities. Then, ranking effects, which are obscured by strong sorting effects in the data at low durations, dominate.

Clearly, the implication that there is considerable heterogeneity between segments leaves some scope for identifying segments and directing labor market policies to those segments that perform badly. On top of this, our analysis shows that, even at a high level of aggregation, within market ranking eventually dominates sorting effects, and is thus of considerable importance as well. The institutional structure of the current U.S. unemployment benefit system seems to account for the consequences of the ranking phenomenon because the length of the unemployment benefit entitlement period depends on the business cycle. Labor market policies directed at long-term unemployment in general can be beneficial. Furthermore, even if ranking is not induced by substantial loss of skills, it may demotivate long-term unemployed, and thus call for similar policies. As ranking is associated with limited adjustment of wages to unemployment, such policies could also be effective in reducing persistence of unemployment at the aggregate level.

Appendix

The sorting process

This appendix provides details on the sorting model. We use discrete duration t and discrete calendar time τ, measured on the time scales introduced in Subsection 3.4. Let c_τ denote the value of the business cycle indicator at calendar time τ, and let $\vartheta(t|c_\tau, v)$ now denote the exit probability from unemployment at calendar time τ and duration t. The distribution function $G(v)$ is such that $\Pr[0 < \vartheta(t|c_\tau, v) < 1] = 1$. We again assume that $\partial\eta(c_\tau, t)/\partial c_\tau > 0$. Denote $\nu(\tau, t) = \mathbb{E}[v|\{c\}_{\tau-1}, T \geq t]$, where $\{c\}_{\tau-1} = \{\ldots, c_{\tau-2}, c_{\tau-1}\}$. The conditional survivor function is given by $S(t|\tau, v) := \Pr(T \geq t|\{c\}_{\tau-1}, v) = \prod_{i=0}^{t-1}(1-\eta(c_{\tau-t+i}, i)v)$, where we adopt the convention $\prod_{i=0}^{-1} x_i = 1$. The unconditional survivor function equals $S(t|\tau) = \mathbb{E}[S(t|\tau, v)] = \mathbb{E}[\prod_{i=0}^{t-1}(1-\eta(c_{\tau-t+i}, i)v)]$, where expectations are taken with respect to $G(v)$, unless conditioning is explicitly denoted. The distribution of v conditional on survival up to t is given by

$$\Pr(V \leq v|\{c\}_{\tau-1}, T \geq t) = \frac{\Pr(V \leq v, T \geq t|\{c\}_{\tau-1})}{S(t|\tau)} = \frac{\int_0^v S(t|\tau, V)\, \mathrm{d}G(V)}{S(t|\tau)}. \tag{20}$$

Thus, we can characterize the conditional distribution of v, say $G(v|\tau, T \geq t)$, by

$$\mathrm{d}G(v|\tau, T \geq t) = \frac{S(t|\tau, v)}{S(t|\tau)}\mathrm{d}G(v) = \frac{\prod_{i=0}^{t-1}(1-\eta(c_{\tau-t+i}, i)v)}{\mathbb{E}\left[\prod_{i=0}^{t-1}(1-\eta(c_{\tau-t+i}, i)v)\right]}\mathrm{d}G(v). \tag{21}$$

Then, the k-th moment of v, conditional on survival up to time t, is given by

$$\mathbb{E}\left[v^k|\{c\}_{\tau-1}, T \geq t\right] = \frac{\mathbb{E}\left[v^k\prod_{i=0}^{t-1}(1-\eta(c_{\tau-t+i}, i)v)\right]}{\mathbb{E}\left[\prod_{i=0}^{t-1}(1-\eta(c_{\tau-t+i}, i)v)\right]}. \tag{22}$$

Now, impose steady state on $\eta(c_\tau, t)$, such that $\eta(c_\tau, t) = \eta(c)$ for each τ and t, and some constant $c = c_\tau$, and $\nu(\tau, t) = \nu(c, t)$. Then, we can use equation (22) to show that

$$\nu(c, t) = \frac{\mathbb{E}\left[v(1-\eta(c)v)^t\right]}{\mathbb{E}\left[(1-\eta(c)v)^t\right]}. \tag{23}$$

Then, duration dependence between duration classes t and $t+1$ can be characterized by $\nu(c, t+1) - \nu(c, t)$. It can be shown that

$$\nu(c, t+1) - \nu(c, t) = -\eta(c)\frac{S(t|c)}{S(t+1|c)}\,\mathrm{var}(v|c, T \geq t). \tag{24}$$

Thus, if the (conditional) variance of v is strictly positive, the expected value of v falls between cohorts in duration classes t and $t+1$. This is the familiar result that unobserved heterogeneity generates negative duration dependence in observed exit probabilities. The marginal effect of a change in c on duration dependence between 0 and t is given by

$$\begin{aligned}
\frac{\partial}{\partial c}\ln\frac{\nu(c, t)}{\nu(c, 0)} &= -\eta_c(c)t\left\{\frac{\mathbb{E}\left[v^2(1-\eta(c)v)^{t-1}\right]}{\mathbb{E}\left[v(1-\eta(c)v)^t\right]} - \frac{\mathbb{E}\left[v(1-\eta(c)v)^{t-1}\right]}{\mathbb{E}\left[(1-\eta(c)v)^t\right]}\right\} \\
&= -\frac{\eta_c(c)t}{1-\eta(c)\mathbb{E}[v|c, T \geq t-1]} \times \\
&\left\{\frac{1-\eta(c)\mathbb{E}[v|c, T \geq t-1]}{1-\eta(c)\mathbb{E}[v^2|c, T \geq t-1]/\mathbb{E}[v|c, T \geq t-1]}\frac{\mathbb{E}\left[v^2|c, T \geq t-1\right]}{\mathbb{E}[v|c, T \geq t-1]} - \mathbb{E}[v|c, T \geq t-1]\right\},
\end{aligned} \tag{25}$$

which is weakly smaller than 0 as $\mathbb{E}\left[v^2|c, T \geq t-1\right] \geq \mathbb{E}\left[v|c, T \geq t-1\right]^2$ and $\eta(c)\mathbb{E}\left[v^2|c, \ \ T \geq t-1\right] < \mathbb{E}\left[v|c, T \geq t-1\right]$ (Shohat and Tamarkin, 1943, and Akhiezer, 1965). If the first inequality holds strictly, *i.e.* if $\text{var}(v|c, T \geq t-1) > 0$, the interaction effect is strictly negative, which proves the claim in the main text.

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Table 1: Incidence model; estimated seasonal effects ($\omega_{g,4}$)

	nonwhite males		**nonwhite females**		**white males**		**white females**	
February	-0.13	(0.03)	-0.08	(0.03)	-0.15	(0.02)	-0.13	(0.02)
March	-0.18	(0.03)	-0.11	(0.03)	-0.25	(0.02)	-0.21	(0.02)
April	-0.16	(0.03)	-0.11	(0.03)	-0.31	(0.02)	-0.23	(0.02)
May	-0.15	(0.03)	-0.01	(0.03)	-0.28	(0.02)	-0.15	(0.02)
June	0.35	(0.03)	0.40	(0.03)	0.05	(0.02)	0.16	(0.02)
July	0.13	(0.03)	0.17	(0.03)	-0.15	(0.02)	-0.03	(0.02)
August	-0.10	(0.03)	0.02	(0.03)	-0.26	(0.02)	-0.02	(0.02)
September	-0.05	(0.03)	0.16	(0.03)	-0.19	(0.02)	0.11	(0.02)
October	-0.08	(0.03)	0.02	(0.03)	-0.24	(0.02)	-0.06	(0.02)
November	-0.09	(0.03)	-0.01	(0.03)	-0.16	(0.02)	-0.10	(0.02)
December	-0.14	(0.03)	-0.15	(0.03)	-0.16	(0.02)	-0.31	(0.02)

Note: Standard errors in parentheses.

Table 2: Duration model; estimation results

group-specific intercepts (γ)								
nonwhite males	-0.75	(0.01)	-0.77	(0.02)	-0.75	(0.01)	-0.69	(0.01)
nonwhite females	-0.63	(0.01)	-0.65	(0.02)	-0.63	(0.01)	-0.57	(0.01)
white males	-0.71	(0.01)	-0.73	(0.02)	-0.71	(0.01)	-0.65	(0.01)
white females	-0.59	(0.01)	-0.61	(0.02)	-0.59	(0.01)	-0.53	(0.01)
baseline duration dependence (ψ_1)								
$\psi_1(1)$	-0.21	(0.02)	-0.17	(0.02)	-0.19	(0.01)	-0.21	(0.01)
$\psi_1(2)$	-0.39	(0.02)	-0.35	(0.03)	-0.38	(0.01)	-0.38	(0.02)
$\psi_1(3)$	-0.62	(0.02)	-0.59	(0.03)	-0.64	(0.02)	-0.58	(0.02)
$\psi_1(4)$	-1.12	(0.06)	-1.15	(0.05)	-1.23	(0.04)	-1.06	(0.04)
baseline cycle outflow ($\psi_{2,c}$)								
β_2	(help wanted index)						0.76	(0.06)
α_1	-0.12	(0.01)	-0.09	(0.04)	-0.08	(0.01)	-0.12	(0.01)
α_2	0.04	(0.01)	0.03	(0.03)	0.04	(0.01)		
α_3	-0.06	(0.01)	-0.05	(0.03)	-0.04	(0.01)		
α_4	-0.05	(0.01)	-0.03	(0.03)	-0.03	(0.01)		
α_5	-0.04	(0.01)	-0.03	(0.03)	-0.02	(0.01)		
α_6	-0.02	(0.01)	-0.01	(0.02)	-0.01	(0.01)		
α_7	0.03	(0.01)	0.01	(0.03)	0.03	(0.01)		
α_8	0.02	(0.01)	0.00	(0.02)	0.02	(0.01)		
α_9	0.02	(0.01)	0.01	(0.02)	0.01	(0.00)		
α_{10}	-0.02	(0.01)	-0.02	(0.02)	-0.02	(0.00)		
α_{11}	0.04	(0.01)	0.01	(0.01)	0.03	(0.00)		
α_{12}	0.04	(0.01)	0.01	(0.01)	0.03	(0.00)		
α_{13}	-0.04	(0.01)	-0.03	(0.01)	-0.03	(0.00)		
α_{14}	-0.00	(0.00)	-0.00	(0.01)	0.00	(0.00)		
α_{15}	0.03	(0.01)	0.01	(0.01)	0.02	(0.00)		
seasonal effect outflow (ω_2)								
April-June	0.07	(0.01)	0.08	(0.01)	0.07	(0.01)	0.07	(0.01)
July-September	0.21	(0.01)	0.21	(0.01)	0.21	(0.01)	0.21	(0.01)
October-December	0.04	(0.01)	0.04	(0.01)	0.04	(0.01)	0.03	(0.01)

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Table 2: (Continued)

seasonal effect composition inflow (ω_3)								
April-June	-0.05	(0.01)	-0.05	(0.01)	-0.05	(0.01)	-0.05	(0.01)
July-September	-0.11	(0.01)	-0.11	(0.01)	-0.11	(0.01)	-0.11	(0.01)
October-December	-0.09	(0.01)	-0.09	(0.01)	-0.09	(0.01)	-0.09	(0.01)
interaction; duration parameters (ξ_1)								
$\xi_{1,0}$	-0.37	(0.09)			-0.13	(0.09)	-0.30	(0.10)
$\xi_{1,1}$	0.46	(0.12)			0.41	(0.08)	0.65	(0.09)
$\xi_1(1)$	-0.37	(0.09)			-0.13	(0.09)	-0.30	(0.10)
$\xi_1(2)$	-0.27	(0.08)			0.16	(0.13)	0.05	(0.15)
$\xi_1(3)$	0.29	(0.11)			0.87	(0.15)	1.04	(0.21)
$\xi_1(4)$	1.32	(0.36)			1.99	(0.26)	2.69	(0.35)
interaction; cycle parameters (ξ_2)								
δ_1	-0.17	(0.06)	-0.01	(0.04)				
δ_2	0.01	(0.08)	0.02	(0.03)				
δ_3	0.06	(0.04)	-0.01	(0.04)				
δ_4	-0.05	(0.07)	-0.02	(0.02)				
δ_5	0.01	(0.03)	-0.00	(0.03)				
δ_6	-0.03	(0.06)	-0.01	(0.02)				
δ_7	0.06	(0.04)	0.03	(0.03)				
δ_8	0.07	(0.04)	0.02	(0.02)				
δ_9	0.06	(0.05)	0.00	(0.02)				
δ_{10}	0.03	(0.03)	-0.01	(0.01)				
δ_{11}	0.07	(0.04)	0.04	(0.02)				
δ_{12}	0.08	(0.03)	0.04	(0.01)				
δ_{13}	0.00	(0.03)	-0.02	(0.01)				
δ_{14}	-0.02	(0.02)	0.00	(0.01)				
δ_{15}	0.11	(0.04)	0.01	(0.01)				
measurement errors								
σ_{nm}	0.23	(0.00)	0.23	(0.00)	0.23	(0.00)	0.24	(0.00)
σ_{nf}	0.23	(0.00)	0.23	(0.00)	0.23	(0.00)	0.24	(0.00)
σ_{wm}	0.14	(0.00)	0.14	(0.00)	0.14	(0.00)	0.15	(0.00)
σ_{wf}	0.13	(0.00)	0.13	(0.00)	0.13	(0.00)	0.14	(0.00)

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Table 2: (Continued)

statistics				
N	$288 \times 4 \times 5$	$288 \times 4 \times 5$	$288 \times 4 \times 5$	$288 \times 4 \times 5$
$\ln \mathcal{L}$	8135.11	8099.00	8102.50	7819.42
R_0^2	0.40	0.42	0.40	0.35
R_1^2	0.20	0.19	0.21	0.19
R_2^2	0.15	0.14	0.14	0.12
R_3^2	0.07	0.07	0.08	0.06
R_4^2	0.06	0.02	0.02	0.03

Note: Standard errors in parentheses. R_i^2 is the pseudo-R^2 for the $i+1$-th equation ($\widetilde{\theta}(i|\tau, g)$).

Table 3: Duration model with cyclical cohort effects: estimation results

group-specific intercepts (γ)				
nonwhite males	-0.75	(0.01)	-0.68	(0.01)
nonwhite females	-0.63	(0.01)	-0.55	(0.01)
white males	-0.71	(0.01)	-0.64	(0.01)
white females	-0.59	(0.01)	-0.52	(0.01)
baseline duration dependence (ψ_1)				
$\psi_1(1)$	-0.21	(0.01)	-0.21	(0.02)
$\psi_1(2)$	-0.39	(0.01)	-0.39	(0.01)
$\psi_1(3)$	-0.62	(0.01)	-0.62	(0.01)
$\psi_1(4)$	-1.11	(0.01)	-1.16	(0.01)
baseline cycle outflow ($\psi_{2,c}$)				
β_2	(help wanted index)			
			0.49	(0.07)
α_1	-0.15	(0.01)	-0.19	(0.02)
α_2	0.05	(0.01)		
α_3	-0.02	(0.01)		
α_4	-0.03	(0.01)		
α_5	-0.02	(0.01)		
α_6	-0.01	(0.01)		
α_7	0.00	(0.01)		
α_8	0.00	(0.01)		
α_9	0.01	(0.01)		
α_{10}	-0.01	(0.01)		
α_{11}	0.03	(0.01)		
α_{12}	0.00	(0.01)		
α_{13}	-0.01	(0.01)		
α_{14}	0.00	(0.00)		
α_{15}	0.01	(0.01)		
seasonal effect outflow (ω_2)				
April-June	0.07	(0.01)	0.07	(0.01)
July-September	0.21	(0.01)	0.20	(0.01)
October-December	0.04	(0.01)	0.04	(0.01)
cycle composition inflow ($\psi_{3,c}$)				
β_3	(help wanted index)			
	0.69	(0.07)	0.51	(0.06)

(table continued on next page)

Table 3: (Continued)

seasonal effect composition inflow (ω_3)				
April-June	-0.05	(0.01)	-0.04	(0.01)
July-September	-0.11	(0.01)	-0.11	(0.01)
October-December	-0.09	(0.01)	-0.10	(0.01)
interaction; duration parameters (ξ_1)				
$\xi_{1,0}$	-0.49	(0.41)	-0.91	(0.07)
$\xi_{1,1}$	0.64	(0.52)	1.10	(0.07)
$\xi_1(1)$	-0.49	(0.41)	-0.91	(0.07)
$\xi_1(2)$	-0.35	(0.30)	-0.72	(0.10)
$\xi_1(3)$	0.44	(0.38)	0.56	(0.17)
$\xi_1(4)$	1.86	(1.53)	2.95	(0.32)
interaction; cycle parameters (ξ_2)				
δ_1	-0.12	(0.11)		
δ_2	0.01	(0.03)		
δ_3	0.05	(0.05)		
δ_4	-0.03	(0.04)		
δ_5	0.01	(0.03)		
δ_6	-0.02	(0.03)		
δ_7	0.05	(0.05)		
δ_8	0.06	(0.05)		
δ_9	0.05	(0.05)		
δ_{10}	0.02	(0.03)		
δ_{11}	0.06	(0.06)		
δ_{12}	0.05	(0.05)		
δ_{13}	-0.00	(0.02)		
δ_{14}	-0.01	(0.02)		
δ_{15}	0.07	(0.06)		
measurement errors				
σ_{nm}	0.23	(0.00)	0.24	(0.00)
σ_{nf}	0.23	(0.00)	0.24	(0.00)
σ_{wm}	0.14	(0.00)	0.15	(0.00)
σ_{wf}	0.13	(0.00)	0.14	(0.00)

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Table 3: (Continued)

statistics		
N	$288 \times 4 \times 5$	$288 \times 4 \times 5$
$\ln \mathcal{L}$	8180.53	7834.93
R_0^2	0.41	0.35
R_1^2	0.21	0.18
R_2^2	0.15	0.12
R_3^2	0.07	0.06
R_4^2	0.06	0.04

Note: Standard errors in parentheses. R_i^2 is the pseudo-R^2 for the $i+1$-th equation $(\widetilde{\theta}(i|\tau, g))$.

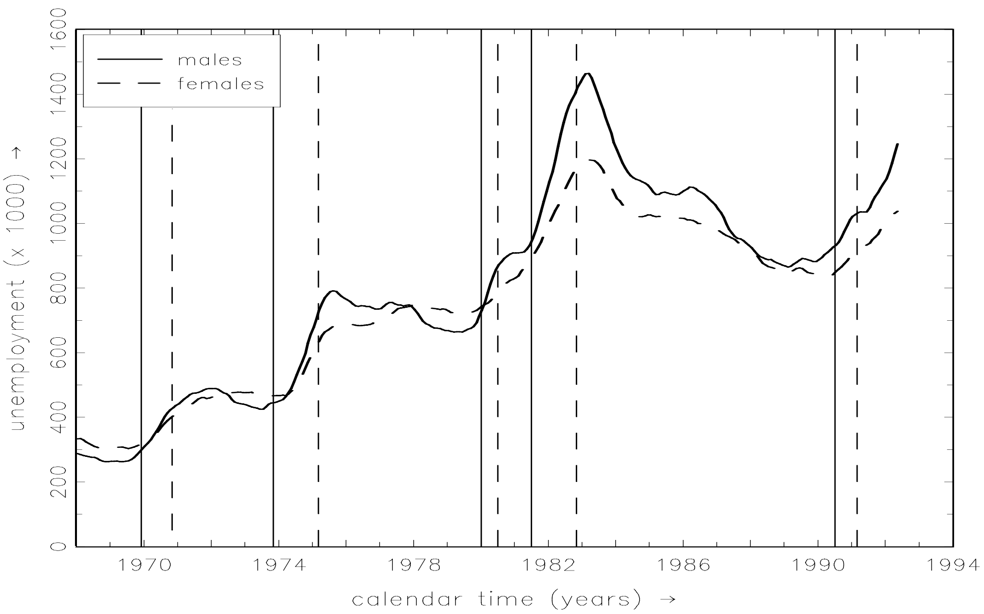
Table 4: Variance decomposition of the log unemployment rate

	variance full cycle (u_5)					
eliminated	**fraction of variance attributed to**					
component	**elimin. comp.**		**remaining comp.**		**covariance term**	
cycle incidence	0.35	(0.36)	0.20	(0.20)	0.45	(0.44)
cycles outflow	0.20	(0.20)	0.35	(0.36)	0.45	(0.44)
	variance full cycle outflow only (u_5)					
eliminated	**fraction of variance attributed to**					
component	**elimin. comp.**		**remaining comp.**		**covariance term**	
contemp. cycle outflow	0.97	(0.98)	0.00	(0.00)	0.02	(0.02)
cycle composition inflow	0.00	(0.00)	0.97	(0.98)	0.02	(0.02)
	variance contemporaneous cycle outflow only (u_5)					
eliminated	**fraction of variance attributed to**					
component	**elimin. comp.**		**remaining comp.**		**covariance term**	
interaction outflow	0.31	(0.15)	2.05	(1.67)	-1.36	(-0.83)
duration dependence	0.17	(0.08)	1.59	(1.30)	-0.76	(-0.38)
	variance contempemporaneous cycle outflow without interaction only (u_5)					
eliminated	**fraction of variance attributed to**					
component	**elimin. comp.**		**remaining comp.**		**covariance term**	
duration dependence	0.02	(0.01)	0.77	(0.78)	0.21	(0.21)
	variance full cycle (u)					
eliminated	**fraction of variance attributed to**					
component	**elimin. comp.**		**remaining comp.**		**covariance term**	
cycle incidence u_5	0.23	(0.24)	0.31	(0.30)	0.46	(0.46)
cycles outflow u_5 and cycle u/u_5	0.31	(0.30)	0.23	(0.24)	0.46	(0.46)

Note: Let u be the unemployment rate series of which the variance is to be decomposed, and $\hat{u}$ the unemployment rate that results if any of the components in the first column is excluded. Then, Columns 2–4 report respectively $\text{var}(\ln(u) - \ln(\hat{u}))$, $\text{var}(\ln(\hat{u}))$, and $2\,\text{cov}(\ln(u) - \ln(\hat{u}), \ln(\hat{u}))$, all divided by $\text{var}(\ln(u))$. In parentheses, similar statistics are given for linearly detrended versions of $\ln(u)$ and $\ln(\hat{u})$.

Figure 1: Unemployment level (12 months moving average)

a. nonwhites



b. whites

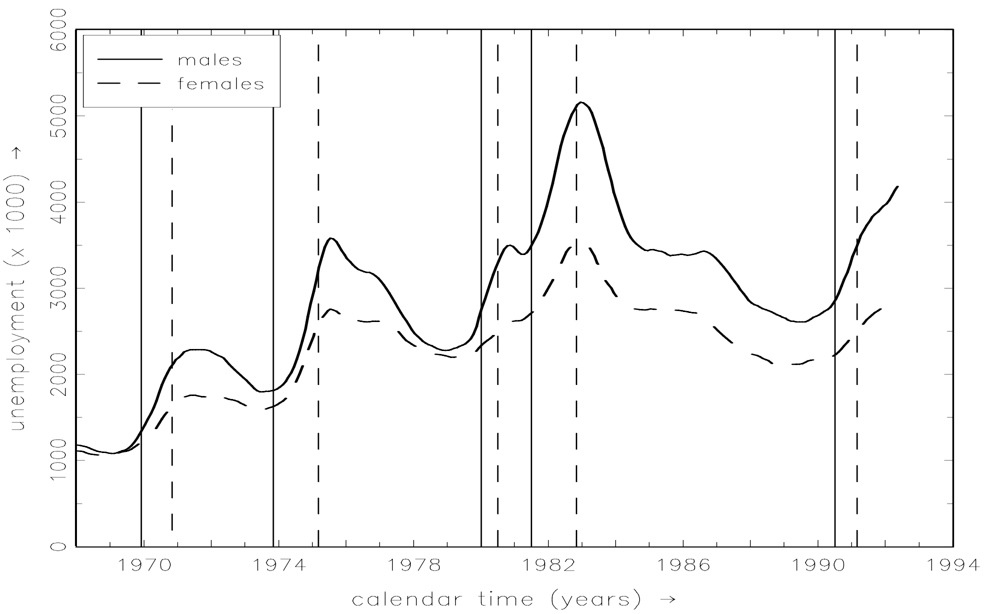


Figure 2: Unemployment rate (12 months moving average)

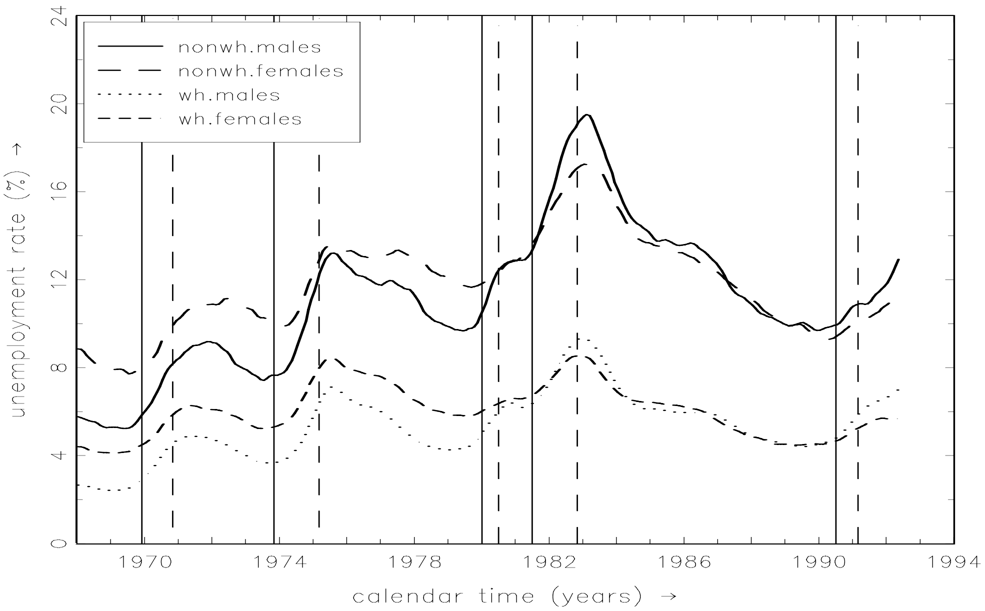


Figure 3: Inflow into unemployment (% of labor force; 12 months moving average)

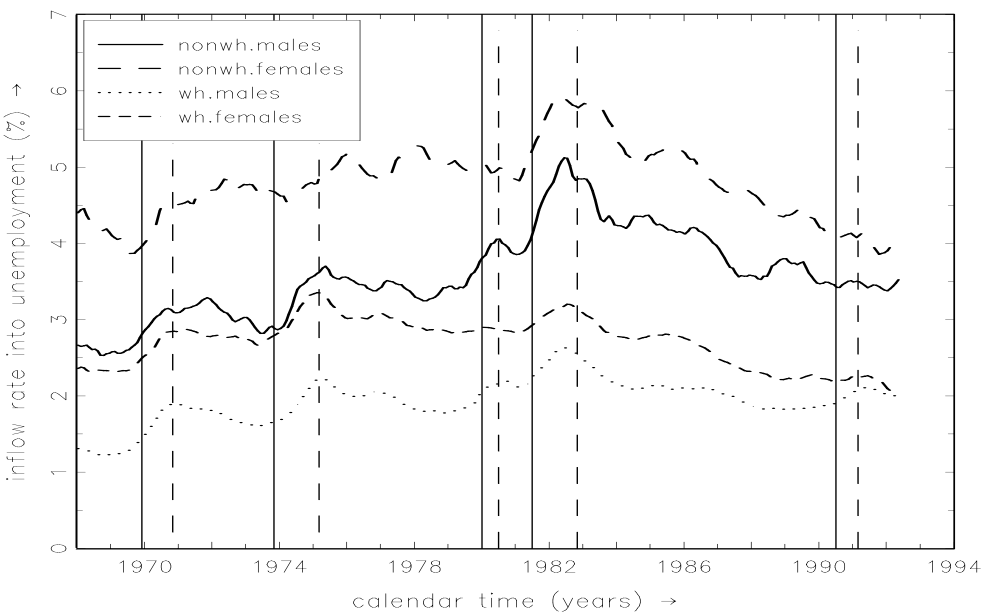


Figure 4: Outflow from unemployment (% of unemployment; 12 months moving average)

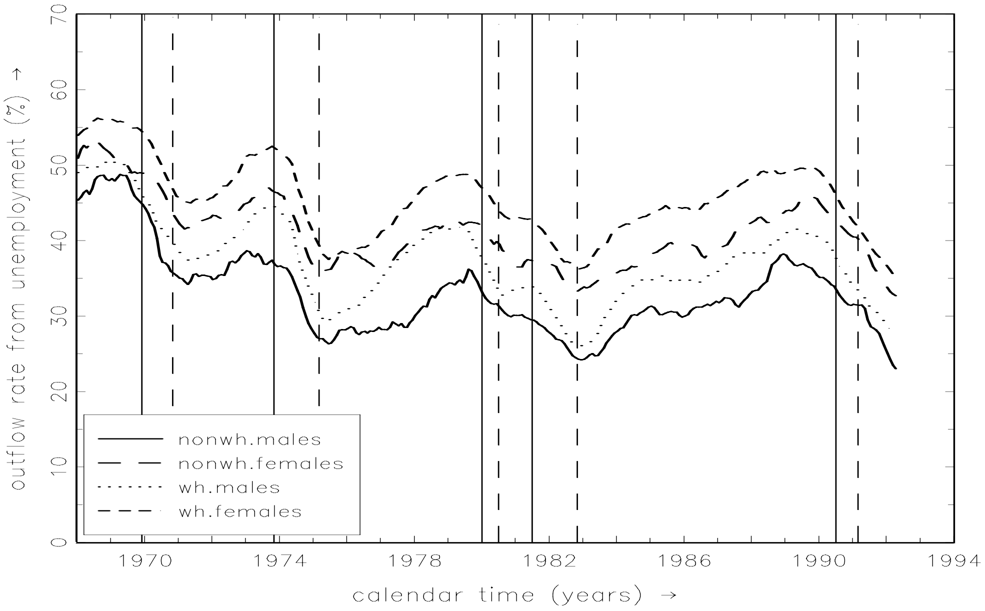


Figure 5: Help wanted index

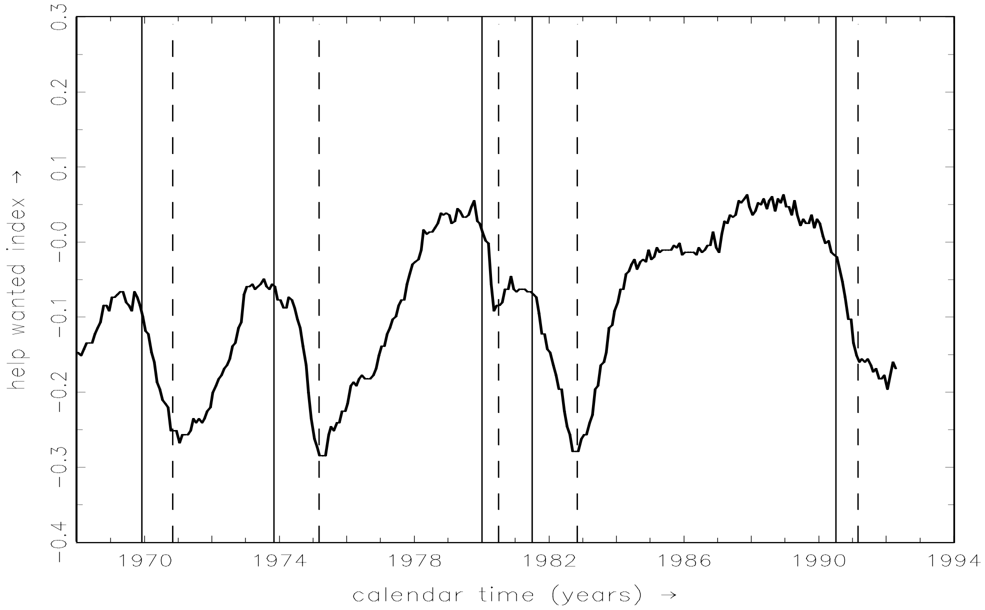


Figure 6: Cycle unemployment incidence rate by demographic group

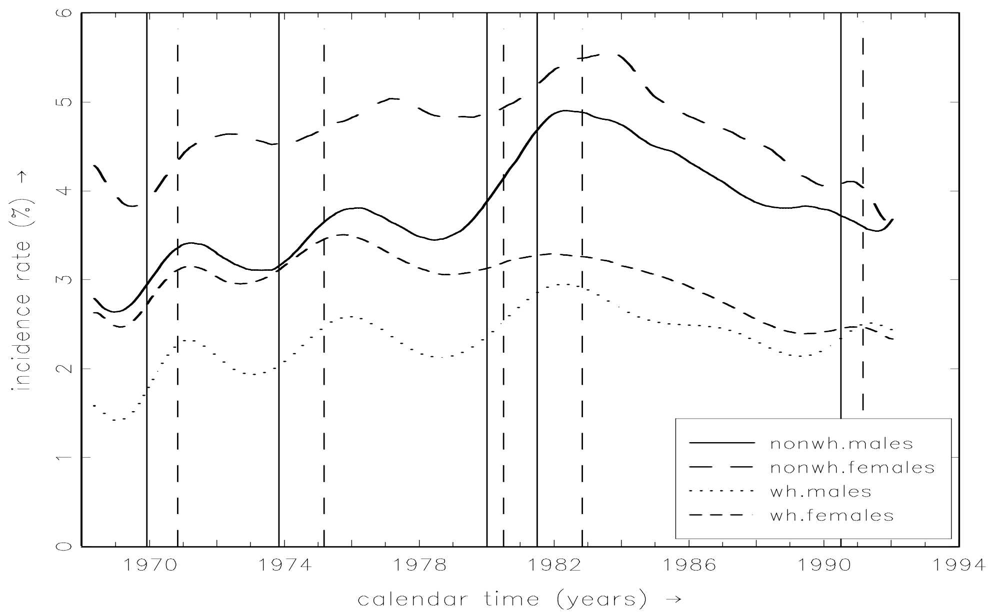
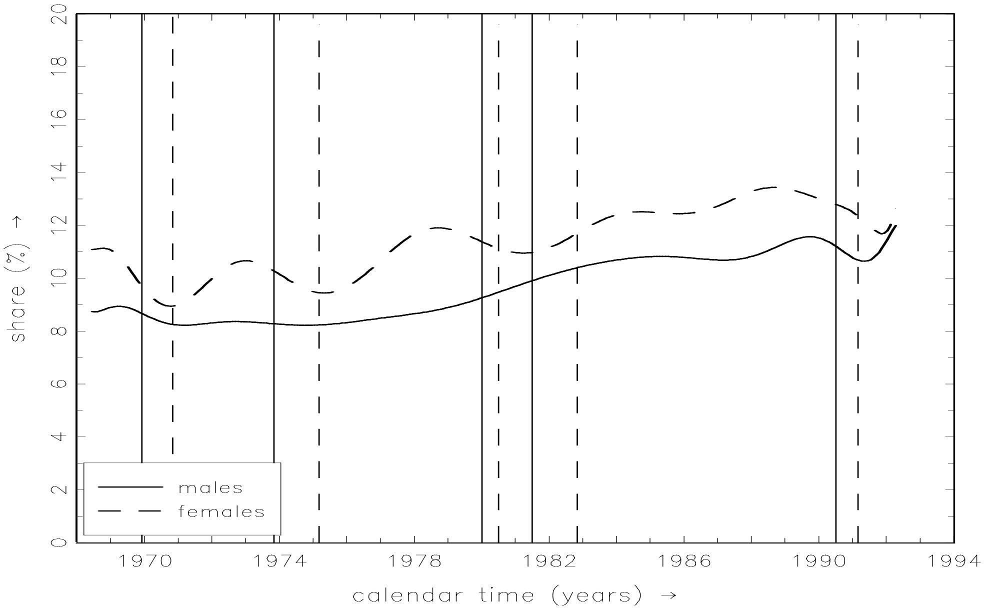


Figure 7: Cycle incidence shares

a. nonwhites



b. whites

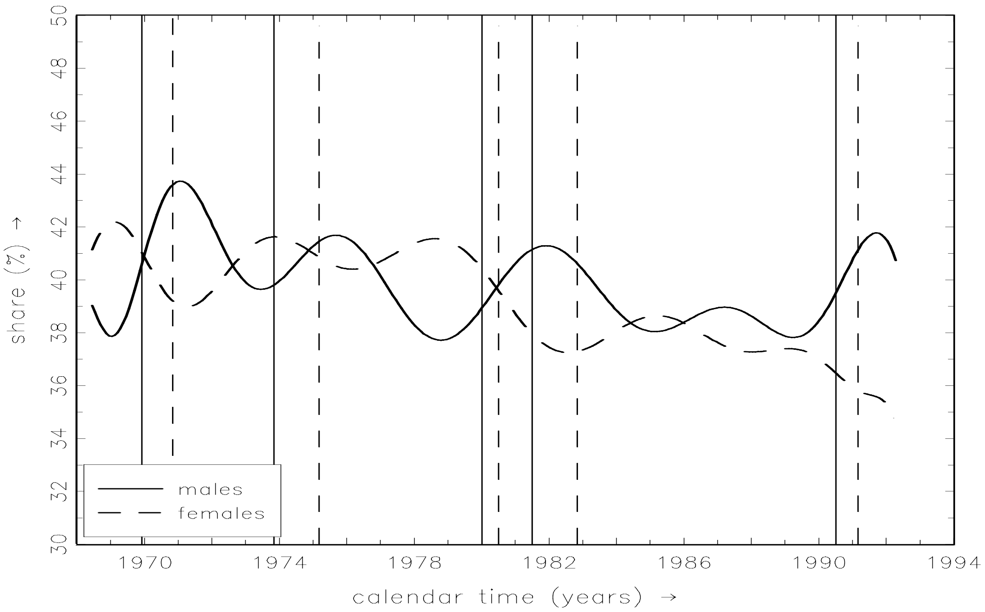


Figure 8: Estimated baseline and interaction cycles in the outflow

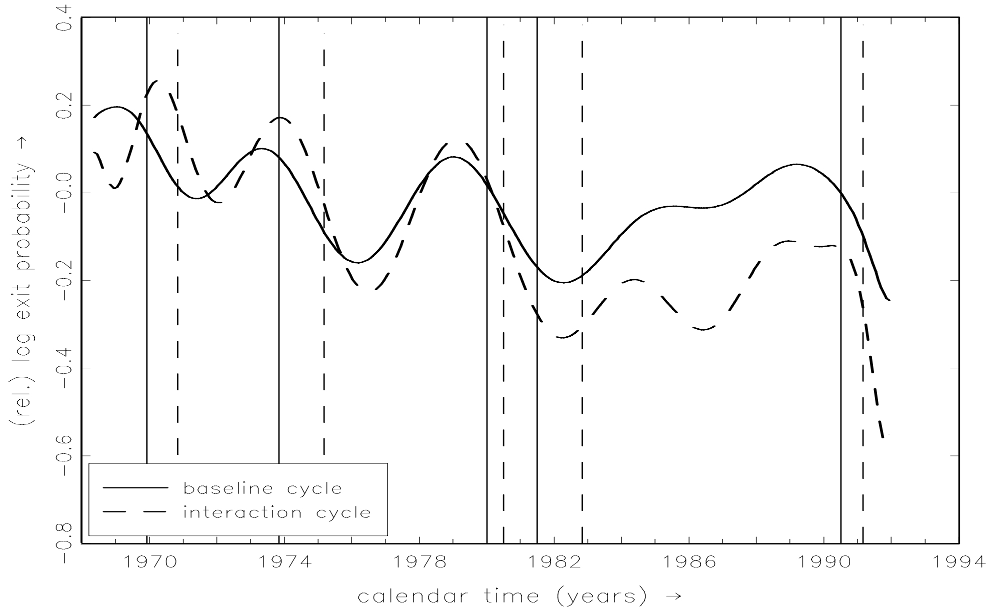


Figure 9: Outflow cycles by duration

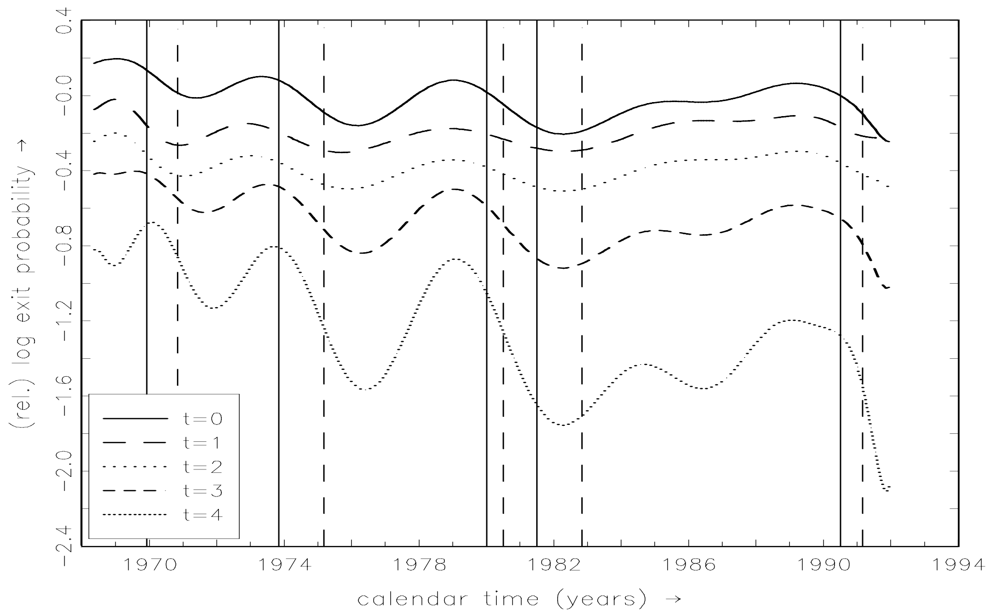


Figure 10: Duration dependence and the outflow cycle

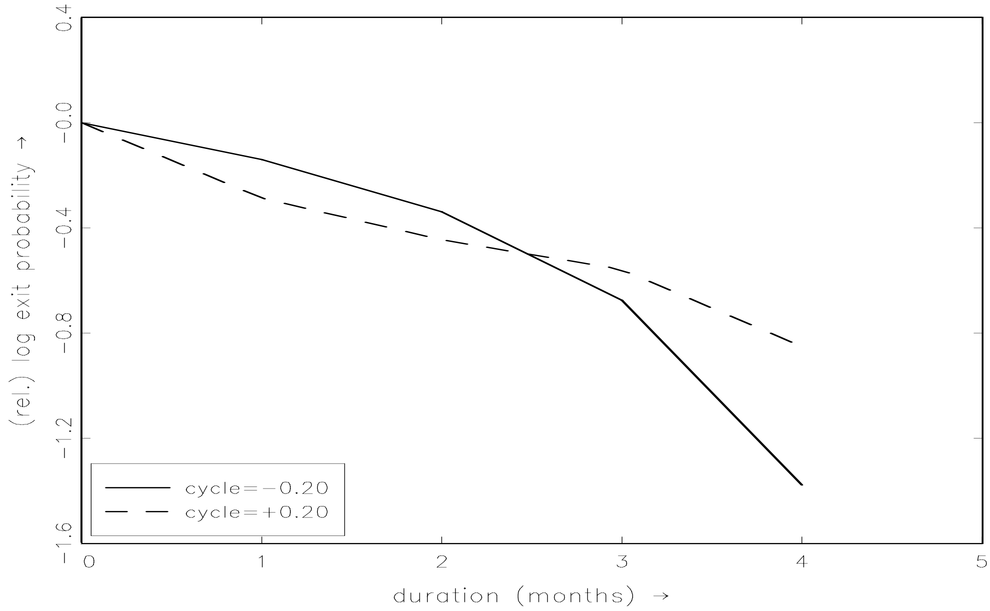


Figure 11: Full unemployment rate (u) and first 6 weeks unemployment rate (u_5; both in 12 months moving averages)

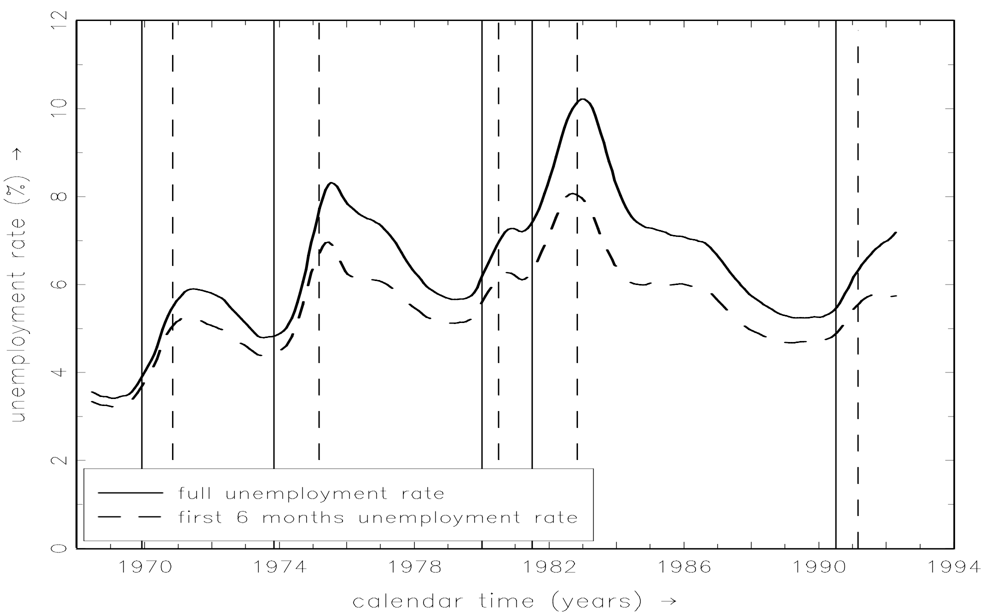


Figure 12: Unemployment rate (u_5); fitted series and data

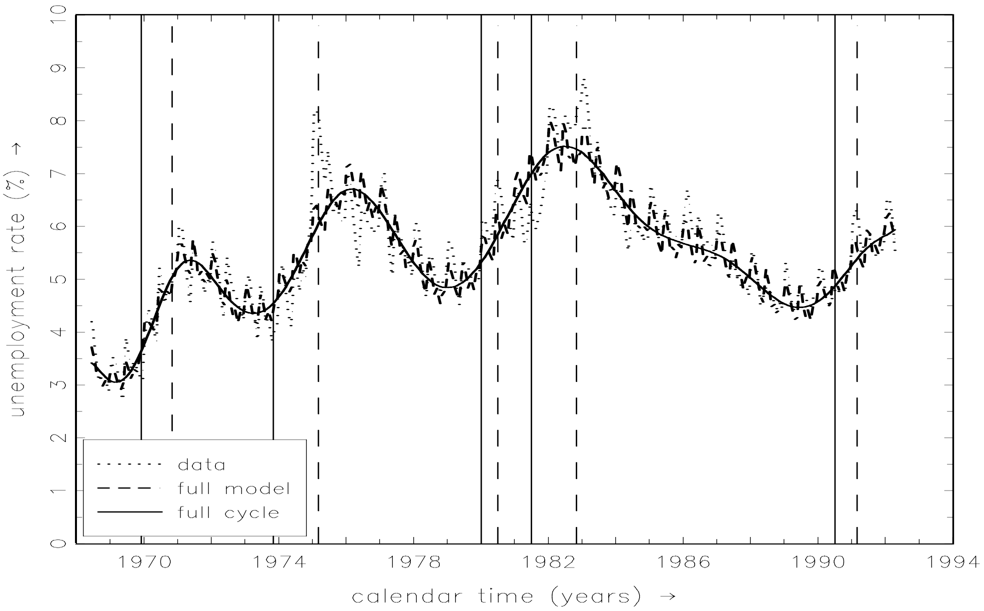


Figure 13: Unemployment rate (u_5); full cycle and without cycle incidence

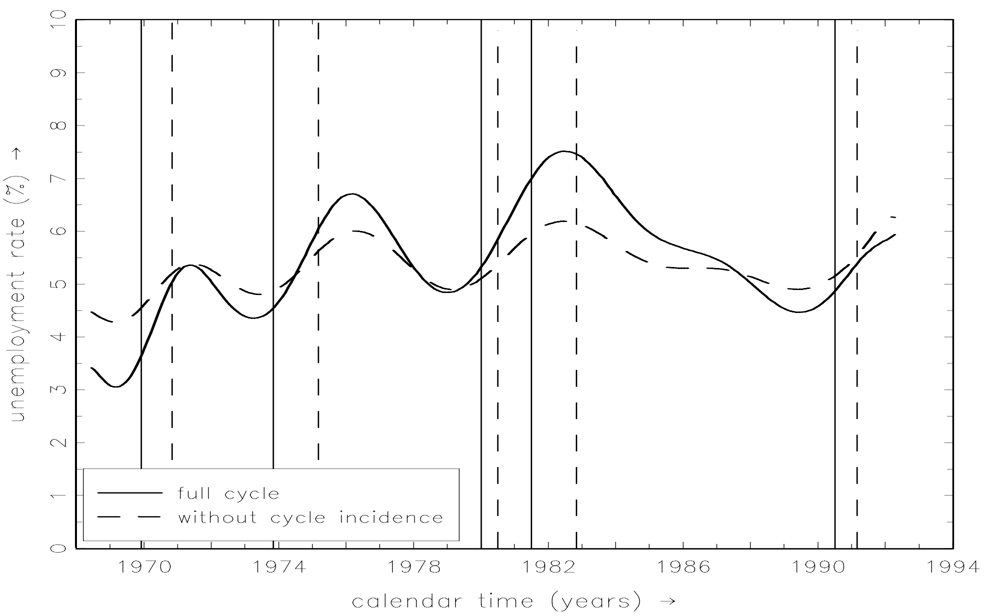


Figure 14: Unemployment rate (u_5); full cycle and without cycles outflow

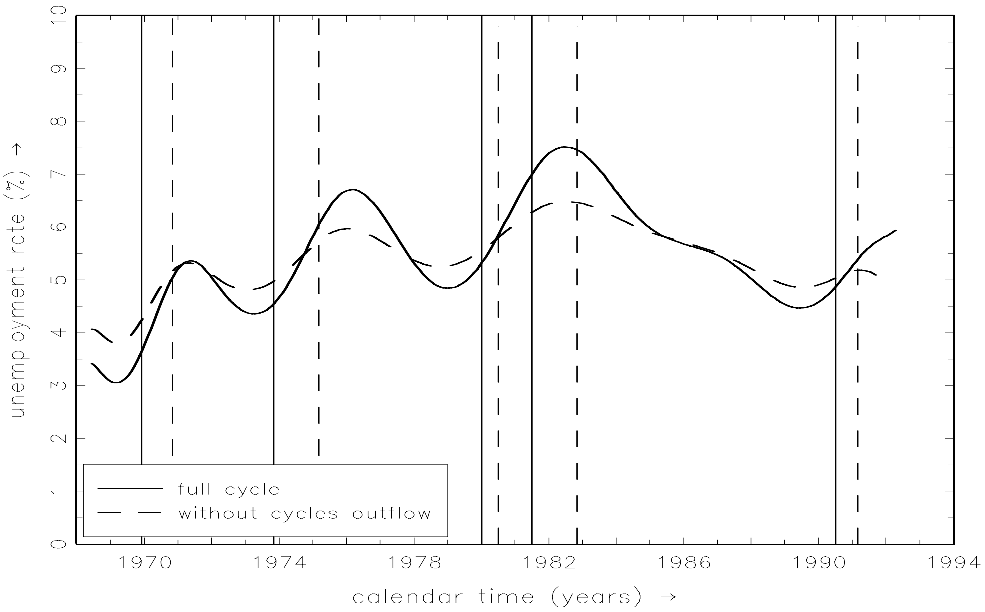


Figure 15: Unemployment rate (u_5); contemporaneous cycle outflow, without interaction, and without duration dependence